Progressive campaigns, social media ads and young voters: Null effects from the 2019 UK General Election

Florian Foos*[†] Peter John[‡] Asli Unan[§]

f.foos@lse.ac.uk peter.john@kcl.ac.uk asli.unan@kcl.ac.uk

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Abstract

Civic organisations and progressive campaigns regard digital ad campaigns as an essential method to register young voters and to change the composition of the electorate. Digital strategies look promising because the registration process can be completed online, in less than five minutes, using a link in the ad. But do typical digital ad campaigns that promote messages that young people's votes matter work? We provide evidence from a large-scale randomised trial embedded in a high-profile social media ad campaign encouraging young people to register to vote before the UK 2019 General Election. We worked with a civil society organisation to deliver online adverts on Instagram and Snapchat, assigning 879 postcode sectors and 149'240 postcodes located within 40 parliamentary constituencies to treatment or control. Despite a wide reach and high engagement rates on social media, we find at best minimal effects of the campaign on young people's voter registrations. We conclude that a commonly-used digital youth voter registration strategy was ineffective in a high profile case when progressive parties' electoral strategy heavily relied on the youth vote.

Keywords: elections | social media | voter registration | youth mobilization

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[†]Department of Government, London School of Economics & Political Science

[‡]Department of Political Economy, King's College London

[§]Department of Political Economy, King's College London

Introduction

Voter registration and turnout among young people are lower than for older citizens (Holbein and Hillygus 2020). They are therefore an obvious target for non-partisan campaigns that aim to increase electoral participation. Due to an increasing age-gradient in party support, progressive campaigns also target young people to change the composition of the electorate (Foos and John 2018; Broockman and Kalla 2020). Left-wing candidates, such as Bernie Sanders (Broockman and Kalla 2020) and Jeremy Corbyn (Prosser et al. 2020) hoped that youth voter mobilisation would make up for predicted losses among moderate voters. Higher turnout among young voters, often referred to as the "youth quake" hypothesis, is said to have contributed to Labour's unexpected strong showing in the UK 2017 General Election (Sloam and Henn 2018).[1] Therefore, how can non-partisan and partisan campaigns effectively register young people who are difficult to contact with conventional voter registration methods, such as canvassing and direct mail, which are also increasingly difficult to deliver during the COVID-19 pandemic? Social media ads appear promising because many young people are active on social media, and in many localities, such as the United Kingdom, and 40 US-States, the registration process can be completed online, in less than five minutes. Since the act of registration does not require as much time and effort as the act of voting (which happens offline), there are hopes that digital ad campaigns can be more effective at voter registration than at turning registered voters out. Social media advertising campaigns have been shown to have, at best, small positive effects on turnout (Jungherr et al. 2020; Bond et al. 2012; Hager 2019b; Haenschen and Jennings 2019).

Typical youth voter mobilisation campaigns are often based on a strategy of raising awareness about the efficacy of young people's vote, employing "cognitive mobilisation" messages such as "Your Vote Matters" or "Don't Miss Out". However, there is scepticism about whether such cognitive mobilisation messages actually work (Holbein and Hillygus 2020; Hersh 2020). Despite these concerns, a lack of robust evidence means that many campaigns keep on relying on exactly these kind of messages using social media platforms.

We provide robust evidence that shows that this type of social media campaign is ineffective at registering young voters. The context of the 2019 UK General Election is instructive because

[1] Though the best available empirical evidence indicates that it probably did not (Prosser et al. 2020).

Labour and the Liberal Democrats hoped to benefit from a surge in youth voter registration. In collaboration with a non-party civil society organisation, we assigned 879 postcode sectors located within 40 UK parliamentary constituencies to two experimental groups: a control and one that received voter registration video ads. These messages were targeted at young people aged between 18-35 years. We collected validated voter registration data from official registers to measure whether social media campaigns targeted towards young people increased voter registration, and changed the composition of the electorate by registering higher numbers of young voters. Despite a high level of engagement with the ads online, we find no effect of the digital campaign on voter registrations, neither overall, nor among young people in particular.

The scarcity of evidence on the effects of digital ads on electoral mobilisation

Despite the increasing prominence of digital methods in election campaigns, and the heavy financial investments that modern campaigns make online (Jungherr et al. 2020; Fowler et al. 2020), randomized control trials of digital media ads are still rare, and do not focus on voter registration (Fowler et al. 2020). Moreover, they are limited to a few social media platforms, such as Facebook and Twitter, and neglect other platforms that are increasingly popular with younger citizens, like Instagram and Snapchat, the social media used in our study. Randomized trials on Facebook using digital ads in the United States and Germany indicate that ads can increase turnout by around 0.5%p (Bond et al. 2012; Haenschen and Jennings 2019; Hager 2019a,b). Beyond turnout, studies show null effects of public or semi-public Facebook and Twitter posts on online and offline political activism (Coppock et al. 2015; Foos et al. 2020).

Experimental studies of voter registration have so far mostly relied on direct mail and door-to-door canvassing. Face-to-face canvassing has been shown to have larger positive effects in the region of 3-5 %p (Nickerson 2015; Braconnier et al. 2017), but is less feasible during the COVID-crisis. Direct mail and postcards have also been employed as effective means of voter registration (Mann and Bryant 2020; John et al. 2015). Voter registration experiments via email and text message explicitly targeted at young people have recorded divergent findings (Nickerson 2007; Bennion and Nickerson 2018; Kölle et al. 2019). Some of the most promising interventions take place within the school context. Studies using classroom presentations in Colleges and High Schools show substantively large increases in youth voter registration (Bennion and Nickerson 2016; Addonizio 2011), but are difficult to scale.

Cognitive and non-cognitive mobilisation

Campaigns targeting young voters tend to assume that voters need to be mobilised by making them aware of the general importance of politics and their role in it. There are good reasons to question the validity of the assumption that young voters lack the motivation to vote (Holbein and Hillygus 2020). Tasks like registration are not completed because they are perceived to be costly, and young voters have difficulty navigating the process (Holbein and Hillygus 2020).

According to this reasoning, common cognitive mobilisation campaigns, such as 'Rock the Vote', are run based on the assumption that a main cause of low youth turnout is youth disengagement from politics. But based on many metrics, young people's interest and engagement with politics has increased in recent decades (Dalton 2007). Young people also have a civic orientation. If people are already cognitively mobilised, then a campaign based on cognitive mobilisation would be bound to fail, especially when citizens do not have the non-cognitive skills to complete a task and go through a bureaucratic process, such as voter registration. By non-cognitive skills we mean the ability to plan, to process information, and then prepare to convert an intention into action, "For new voters, the registration requirement, in particular, is recognised as especially burdensome – it typically must be completed by a certain deadline, it must be updated with every change in address" (Holbein and Hillygus 2020, p.33). Messages that might help individuals complete the process may be more effective, but typically campaigns focus on cognitive mobilisation (Ahmed 2019).

Research Design

We worked with a civic organisation, Vote for Your Future (VFYF, `https://www.vfyf.co.uk`), randomly assigning a part of its well-organised campaign to test if social media ads are effective at registering young people to vote in the UK 2019 General Election.[2][3] We assigned 879 postcode sectors located within 40 UK parliamentary constituencies (see Appendix A4 for more information about the constituencies) to two groups: one control, and one treatment group that received voter registration ads from VFYF via Instagram and Snapchat. Typical example ads used in the trial by the organisation are displayed in Figure A1 in the Appendix. All ads contained a direct link (via swipe-up on Instagram) to the UK Government's voter registration website (https://www.gov.uk/register-to-vote). Voter registration in the UK can be done by completing an online form requiring name, address, nationality, date of birth, National Insurance Number[4], and e-mail address. The entire process can be completed online, in one session, lasting around five minutes. Hence, the voter registration process is very similar to the process employed in the 40 US states plus DC, that allow for digital voter registration.[5] Adverts were targeted at young people aged between 18 and 35 years. The registration messages appeared in postcode sectors assigned to the treatment group in the week before the voter registration deadline on 26 November. To avoid spillovers, ads were displayed in the mornings and evenings only. VFYF also provided data on the successful placement of ads in each postcode sector, as well as spending, impressions, and engagement metrics at the campaign level. We summarise these online engagement statistics in Table 1.

Table 1: Campaign statistics

Postcode sectors successfully targeted	394/437
Spend Instagram	£4423.52
Spend Snapchat	£3535.09
Total impressions	2,058,431
Total clicks	18,421

Table 1 shows that VFYF spent almost £8,000 on Instagram and Snapchat ads over 7 days, earning more than 2 million impressions and more than 18 thousand clicks. The budget for the entire

[2]It is important to emphasise that we did not evaluate the entire campaign run by VFYF. We did not randomly assign the campaign in their highest priority seats, and we did not run policy-based ads. The 40 constituencies in the experimental sample still contained large numbers of young voters and a mix of seats ranging from majorities smaller than 1% to majorities greater than 10%. We do not find that campaign effects vary conditional on marginality in the sample of seats that were included in the experimental sample.

[3]As pre-registered, we also intended to test if Get-Out-The-Vote reminders sent via social media 2-3 days before the election amplified the campaign's effect on turnout, but we were unable to obtain validated voter turnout data for 37 out of 40 constituencies. Since the GOTV messages were sent after the voter registration deadline, the voter registration outcomes reported in this paper could not have been influenced by GOTV ads. We address deviations from the Pre-Analysis Plan in Appendix E

[4]If the NI number is unavailable, eligibility can be verified via other means, e.g. a passport scan.

[5]For a list of all US states that employ digital voter registration, see https://www.usa.gov/register-to-vote.

campaign was £10,000 but this was not entirely exhausted, indicating that the amount committed was enough to saturate Instagram and Snapchat for the week. There are strict spending limits in place in UK elections, and campaign spending per candidate is capped at a maximum of £30,000 per Parliamentary constituency. As shown in Table 1, the campaign had a wide reach, and lead to a lot of online engagement from young people. The question is whether social media clicks translated into voter registration. After the election, we obtained de-identified voter registration data from the public registers in the 40 constituencies that made up the experimental sample, and matched them to our experimental assignment via the postcode column (the data was de-identified at the individual level, the smallest unit was the postcode). One of the challenges of measuring voter registration in the UK and the US is that the denominator (the number of voting eligible citizens living in a given postcode sector at a given point in time) is difficult to estimate, and we only observe the citizens who register to vote. In our main specification, we therefore count the absolute numbers of registered voters post-treatment in each postcode and postcode sector. Since this specification is relatively noisy, in additional specifications, we use local population estimates for 2019 from the Office of National Statistics (ONS) in the denominator. These estimates do not fully capture all eligibility criteria (Irish and Commonwealth citizens who are residents are for instance allowed to vote in UK elections, but EU citizens are not), but they reduce noise in the estimates.

We describe in detail how we deal with non-reporting postcode sectors (which are missing because most of the postcode sector was located outside of the experimental sample) in Appendix A.3 and Table A2. As expected given random assignment, we find no significant differences in whether control and treatment sectors report voter registration numbers, indicating that missingness is unlikely to have occurred as a function of the treatment. Balance checks are displayed in Figure A2 in the Appendix and show that census covariates are balanced across treatment and control sectors.

Estimation

For the main analyses, we estimate the Intent-to-Treat (ITT) effect using linear regression with heteroskedasticity-robust (HC2) standard errors:

$Y_s = \alpha + \beta_1 RegistrationAd_s + \gamma Constituency_s + \epsilon_s$ (1)

where Y is the absolute number of registered voters per postcode sector s, $RegistrationAd$ is whether a postcode sector s was assigned to receive voter registration ads on Snapchat and Instagram, and $Constituency$ are constituency fixed effects. Recall, that the level of assignment and the level of outcome measurement overlap. Beyond scaling the dependent variable by population, we apply two strategies to improve the precision of the estimates: We report the covariate-adjusted ITTs including the size of the postcode sector (4 categories from large to small), and the following pre-treatment covariates that we obtained from the 2011 census and aggregated to the postcode sector level: share of voters above 35, the proportion of voters who are BAME, the proportion of voters with a university education, and population density. A descriptive summary of the variables used in the subsequent analyses is displayed in Appendix Table A1. The covariate-adjusted ITT is estimated as follows:

$$Y_s = \alpha + \beta_1 RegistrationAd_s + \gamma Constituency_s + \delta X_s + \epsilon_s \quad (2)$$

where X is the N-by-k matrix of pre-treatment covariates.

Second, we also run models (1) and (2) with the outcome data aggregated at the postcode level instead of the postcode sector level. This is the smallest possible unit of measurement in our case.

$$Y_{p,s} = \alpha + \beta_1 RegistrationAd_{p,s} + \gamma Constituency_{p,s} + \epsilon_{p,s} \quad (3)$$

$$Y_{p,s} = \alpha + \beta_1 RegistrationAd_{p,s} + \gamma Constituency_{p,s} + \delta X_{p,s} + \epsilon_{p,s} \quad (4)$$

In models (3) and (4) we cluster the standard errors at the level of assignment, the postcode sector s. As a robustness check, we log-transform the dependent variables in equations (1)-(4) and report the results in Appendix Tables A7 and A9.

In Figure 2 we re-scale the dependent variable to have a mean of 0, and a standard deviation of 1 in the control group. We then re-estimate equations (1) - (4) and plot the estimated treatment effects for all registrations combined and for the subset of registrations where we can identify that the registered voter is between 18 and 35 years of age.

Results

Figure 1 displays the key results graphically. The first column in Figure 1 shows the number of young people (18-35 years) registered in each reporting postcode sector, based on (incomplete) age data that is included on the registers. Individual age data are available for 20% of all registrations.

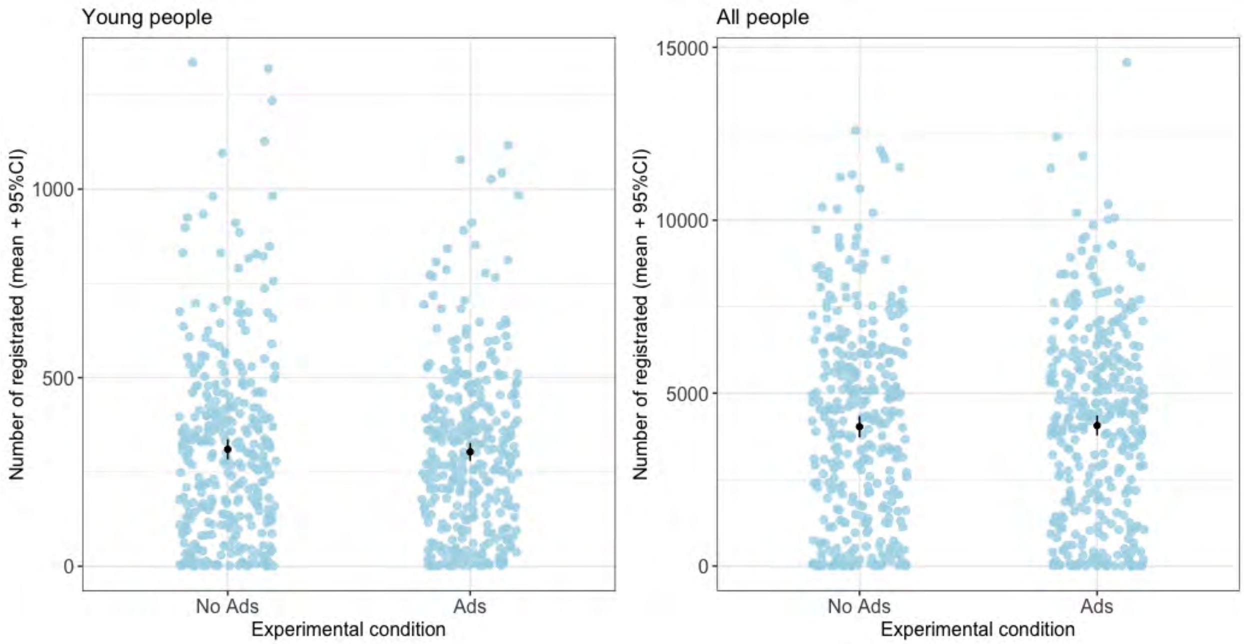

Figure 1: Mean plots with 95% CI; (N = *717*).

The second column displays the absolute number of voters in each reporting postcode sector in treatment and control groups including all observations from the register. Each dot on the plot represents one postcode sector. We also display the means and the surrounding 95% confidence intervals in treatment and control sectors. Figure 1 clearly shows that there are only minimal differences in the means across treatment sectors, where ads were assigned to be displayed, and control sectors, were ads were not displayed. Tables A3-A10 show the full regression results under different specifications estimated at the postcode sector and postcode levels.

In additional specifications, we standardise the dependent variable by 2019 population estimates at the postcode sector level to vary between 0 and 1, dividing the number of registered voters by the number of estimated residents in a given postcode sector (counting residents aged 18-35 for young voters and residents older than 18 for all voters and residents). Our null results are robust to these specifications (see Tables A11-A14). We also report interactions with three pre-treatment covariates: mean age of the postcode sector (column 4 in Tables A3-A10), population density at the postcode sector (Table A15) and all candidates' combined ad spending in the preceding 2017 General Election (Table A16). We do not find any substantively meaningful or statistically significant heterogeneous treatment effects, indicating that the effects of the social media ad campaign were

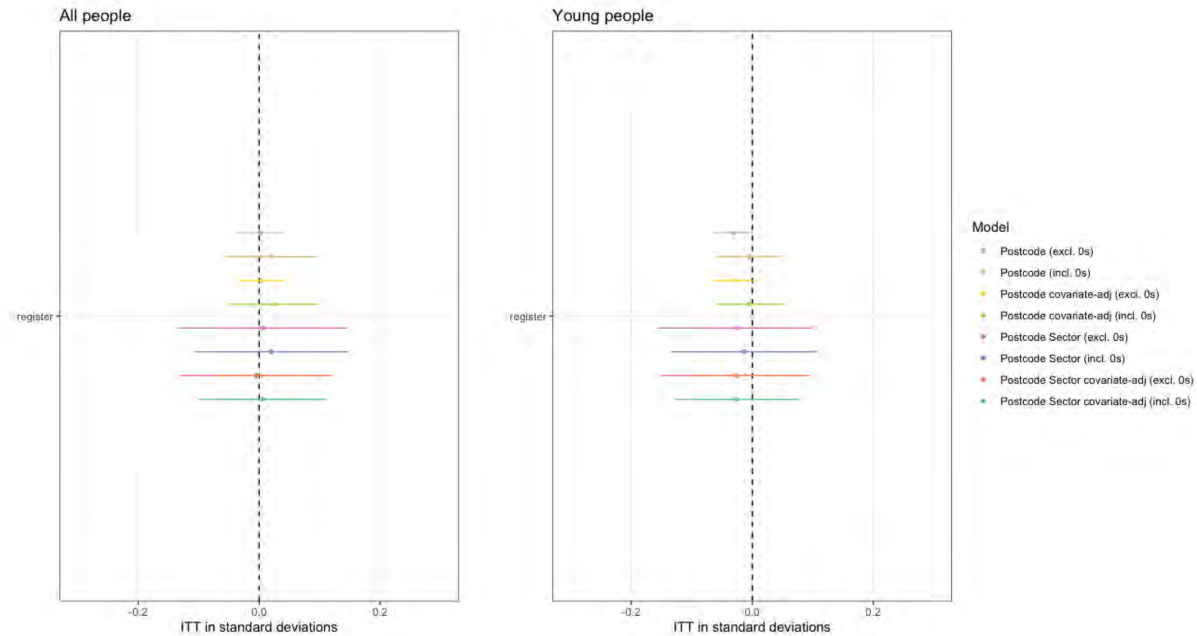

Figure 2: SD plot (N = *879/717* at postcode sector level and N= *149,240/90,678* at postcode level)

minimal across different subgroups and electoral contexts.

To facilitate interpretation of effect sizes, in Figure 2 we re-scale the dependent variable to have a mean of 0, and a standard deviation of 1 in the control group. That means the treatment effects plotted in Figure 2 can be interpreted as the treatment effect in standard deviations. The panel on the left displays the results for the complete sample and the column on the right plots the ITTs sub-setting the count in the dependent variable to those registrations that explicitly indicate that the registrant was aged 18-35 years. All details on estimation can be found in Materials and Methods. Tables A3 through A10 show the full regression results at the postcode sector level and Tables A17 through A20 show the results at the postcode level. Figure 2 indicates that the estimated null effects are centered around 0. The Complier Average Causal Effects (CACE), where we use assignment to treatment as the exogeneous variable and successful ad placement as the endogeneous variable in an IV regression framework, are displayed in SI Appendix Table A21. Since ad placement was successful in 90% of the cases, CACEs differ just slightly from the ITTs reported in Table A21.

Conclusion

This study provides a consistent and sobering picture of the effects of a typical and well-run social media ad campaign aimed at registering young people in a high salience election. We use social media platforms that are particularly popular with young people, Instagram and Snapchat, which have received little attention from researchers conducting randomised campaign trials. Our results show that social media-based cognitive mobilisation messages aimed at young voters were ineffective. We can rule out medium to large effects on young people's voter registration rates, an outcome that should be easy to affect via digital ads. The causal evidence we provide raises questions about whether increasing the electoral participation of young voters via social media is a promising electoral strategy, at least in General Elections (Broockman and Kalla 2020). Of course, the busy campaign environment of a General Election may have contributed to the null effects we observe because ads compete for attention with other campaign messages (Kalla and Broockman 2017). What would speak against this hypothesis is that the ads received a large number of online impressions and clicks. It is nevertheless possible that digital ads could prove to be more effective in local or regional elections.

Did the campaign fail because of the medium, the message, or a combination of medium and message? What we can conclude from this study is that social media ads aimed at cognitive mobilisation - at increasing young people's motivation to vote - did not translate into higher registration numbers. There is potential for non-cognitive strategies that do not focus on increasing the motivation to vote, but on translating young people's existing motivations into political action (Holbein and Hillygus 2020). This aim could for instance be achieved by helping young people effectively navigate the voter registration process, and by sending them tangible reminders of deadlines. Given that social media platforms are likely to remain the media of choice for many organisations, we see trialling different non-cognitive voter registration messages as a key change that could be implemented immediately.

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Appendix

A Materials and Methods

A.1 Voter Registration Ads

In Figure A1 we present typical example ads used in the trial by the organisation.

Figure A1: Voter Registration Ads

A.2 Descriptives

In Table A1 we present descriptive statistics.

Table A1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
N	879	3,239.24	3,002.71	0	61	5,391	14,564
N young	879	235.51	242.99	0	2.5	376	1,336
N with NA	717	3,971.11	2,854.09	1	1,426	5,854	14,564
N young with NA	684	302.65	235.69	1	117	423	1,336
Postcode sector size	879	169.99	79.24	1	135.5	221	388
Advertising spending	879	3,466.28	2,719.66	249.12	1,485.98	4,940.99	11,545.45
Mean age	879	38.84	3.86	26.60	36.60	41.20	54.90
Population density	879	48.81	49.23	0.06	11.45	61.20	344.60
University educated proportion	879	0.27	0.13	0.04	0.18	0.31	0.89
White ethnicity proportion	879	0.80	0.18	0.05	0.72	0.98	1.00
BAME proportion	879	0.20	0.18	0.001	0.02	0.28	0.95

A.3 Missing outcome data

We need to deal with postcode sectors that have missing registration data in our sample because they were (at least partially) located within more than one parliamentary constituency. Only a small number of the 40 constituencies VFYF targeted were bordering each other, and if this was the case, VFYF only included postcode sectors that could be individually allocated within one constituency. However, in a relatively small number of cases, the largest part of a postcode sector was located in a constituency which was not part of the experimental sample and we were therefore unable to obtain registration data on it. We deal with the latter challenge by using two versions of the outcome variable. First, we impute 0s when no registration was reported in a postcode sector, and second we drop postcode sectors that do not report registrations from the analysis (under the assumption that register data is incomplete due to the fact that the respective non-reporting postcode sector was mostly located in parliamentary constituencies outside of the experimental sample, and missingness is not a function of treatment assignment). Consistent with the latter assumption, in Table A2 we report the results of differential attrition checks, where we regress non-reporting on treatment assignment. As should be expected given random assignment, we find no significant differences in reporting voter registration numbers in treatment and control group, indicating that missingness is unlikely to have occurred as a function of the treatment.

Table A2: Sectors with no registrations

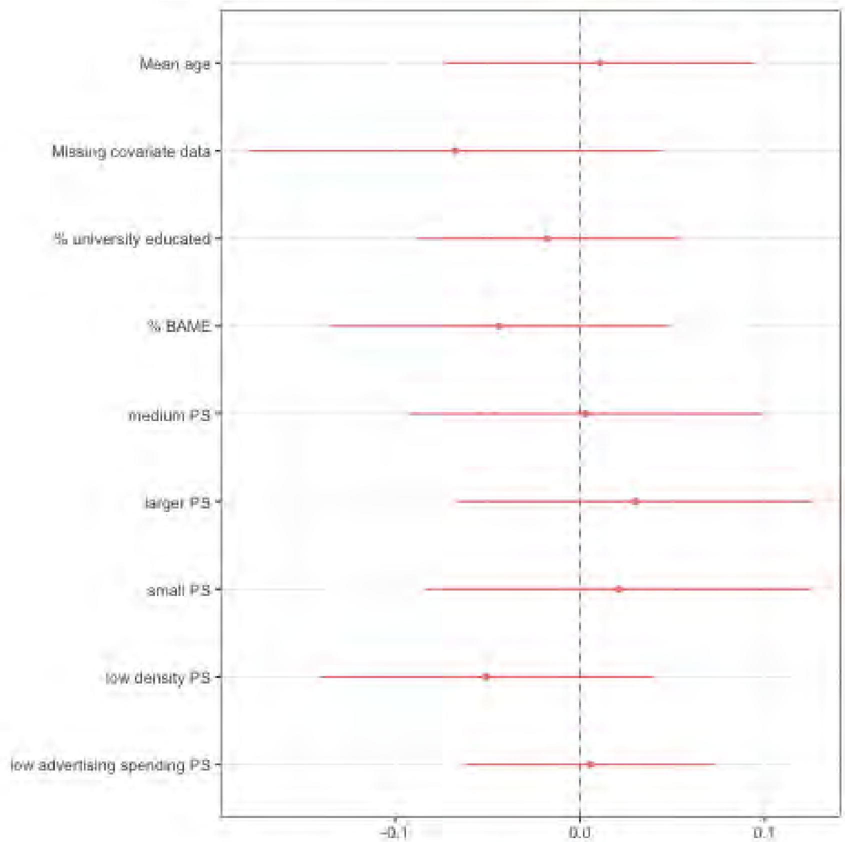
	(1)	(2)	(3)	(4)
(Intercept)	0.12	−0.05	−0.26*	−0.31
	(0.07)	(0.07)	(0.13)	(0.16)
Registration ads	−0.00	0.00	0.01	0.10
	(0.03)	(0.02)	(0.02)	(0.17)
Postcode sector size medium1		0.05*	0.07**	0.07**
		(0.02)	(0.02)	(0.02)
Postcode sector size medium2		0.02	0.04	0.04
		(0.02)	(0.02)	(0.03)
Postcode sector size small		0.50***	0.31***	0.31***
		(0.04)	(0.03)	(0.03)
Mean age			0.00	0.01
			(0.00)	(0.00)
Missing covariate data			0.47***	0.44***
			(0.04)	(0.05)
University educated			0.05	0.04
			(0.10)	(0.10)
BAME			0.00	0.00
			(0.06)	(0.06)
Low density			−0.00	−0.00
			(0.03)	(0.03)
Registration ads: Mean age				−0.00
				(0.00)
Registration ads: Missing covariate data				0.06
				(0.06)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.10	0.36	0.50	0.51
Adj. R^2	0.06	0.32	0.48	0.48
Num. obs.	879	879	879	879
RMSE	0.38	0.32	0.28	0.28

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

A.4 Balance Checks

In Figure A2 we display balance checks, based on a regression of treatment assignment on the covariates recorded in the 2011 census. As expected, we do not find any covariate imbalance between treatment and control groups.

Figure A2: Covariate balance between treatment and control sectors with 95% CIs (N = *879*)



B Results

B.1 Regression tables

Table A3: Number of registrations

	(1)	(2)	(3)	(4)
		Excluding missing sectors		
(Intercept)	2983.11***	4675.02***	7692.78***	7766.94***
	(488.29)	(480.24)	(1307.23)	(1639.35)
Registration ads	17.95	−4.68	−14.32	−193.89
	(208.09)	(188.64)	(188.61)	(1808.69)
Registration ads: Mean age				3.45
				(46.13)
		Including missing sectors		
(Intercept)	2602.31***	4763.64***	8430.02***	8626.17***
	(475.17)	(460.78)	(1272.65)	(1560.35)
Registration ads	62.53	39.10	18.49	−404.85
	(198.70)	(168.09)	(164.67)	(1812.38)
Registration ads: Mean age				9.50
				(46.18)
Sector size covariate	No	Yes	Yes	Yes
Census covariates	No	No	Yes	Yes
Constituency fixed effects	Yes	Yes	Yes	Yes
R^2	0.08	0.34	0.37	0.37
Adj. R^2	0.04	0.31	0.34	0.34
Num. obs.	879	879	879	879
RMSE	2947.89	2494.09	2444.46	2446.69

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A3 confirms this result based on formal hypothesis testing. The differences-in-means estimated in Table A3 based on equations (1) and (2) are small and not statistically significant. They are consistent no matter if we drop postcode sectors that do not report registrations. As a robustness check, Table A7 in the Appendix displays the same analysis with a logged dependent variable. Again, the results are consistent with the conclusion that the campaign did not increase registration. As we would expect given random assignment across 100s of postcode sectors, including pre-treatment covariates does not substantially alter the estimate of the treatment effect, but improves precision. Table A3 also shows that the interaction between mean age measured in the 2011 census and treatment assignment is positive, but small and not statistically significant by any conventional standard.

B.1.1 All voters

Tables A4 and A5 show full regression tables when missing sectors are included and when missing sectors are excluded, respectively. Table A6 demonstrates results with a standardized dependent variable and Table A7 shows results with a logged dependent variable.

Table A4: All registrations (Including missing sectors)

	(1)	(2)	(3)	(4)
(Intercept)	2602.31***	4763.64***	8430.02***	8626.17***
	(475.17)	(460.78)	(1272.65)	(1560.35)
Registration ads	62.53	39.10	18.49	−404.85
	(198.70)	(168.09)	(164.67)	(1812.38)
Postcode sector size medium1		−2291.59***	−2385.12***	−2380.30***
		(286.67)	(284.81)	(285.62)
Postcode sector size medium2		−1127.06***	−1193.86***	−1192.47***
		(297.63)	(295.38)	(295.58)
Postcode sector size small		−4432.12***	−3827.26***	−3830.45***
		(265.89)	(274.93)	(275.02)
Mean age			−76.24*	−80.38*
			(30.19)	(38.11)
Missing covariate data			−1637.42***	−1775.07***
			(276.87)	(338.87)
University educated			−761.33	−765.51
			(811.28)	(815.23)
BAME			−229.80	−246.33
			(487.75)	(486.62)
Low density			−484.69	−486.84
			(262.82)	(263.24)
Registration ads: Mean age				9.50
				(46.18)
Registration ads: Missing covariate data				286.11
				(338.46)
R^2	0.08	0.34	0.37	0.37
Adj. R^2	0.04	0.31	0.34	0.34
Num. obs.	879	879	879	879
RMSE	2947.89	2494.09	2444.46	2446.69

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A5: All registrations (Excluding missing sectors)

	(1)	(2)	(3)	(4)
(Intercept)	2983.11***	4675.02***	7692.78***	7766.94***
	(488.29)	(480.24)	(1307.23)	(1639.35)
Registration ads	17.95	−4.68	−14.32	−193.89
	(208.09)	(188.64)	(188.61)	(1808.69)
Postcode sector size medium1		−2198.19***	−2235.21***	−2222.70***
		(287.51)	(286.98)	(289.15)
Postcode sector size medium2		−1064.54***	−1072.58***	−1073.04***
		(291.33)	(293.63)	(293.67)
Postcode sector size small		−3612.91***	−3518.50***	−3505.89***
		(292.87)	(288.84)	(291.05)
Mean age			−59.46	−60.91
			(31.23)	(40.42)
Missing covariate data			−906.93*	−1143.55*
			(402.63)	(522.84)
University educated			−913.33	−909.54
			(897.30)	(900.30)
BAME			−444.06	−452.05
			(576.77)	(574.70)
Low density			−363.28	−371.29
			(288.16)	(289.25)
Registration ads: Mean age				3.45
				(46.13)
Registration ads: Missing covariate data				552.44
				(684.33)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.11	0.27	0.28	0.28
Adj. R^2	0.06	0.22	0.23	0.22
Num. obs.	717	717	717	717
RMSE	2771.07	2520.75	2511.92	2514.50

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A6: All registrations (Standardized DV)

	(1)	(2)	(3)	(4)
(Intercept)	−0.20	0.51***	1.71***	1.78***
	(0.16)	(0.15)	(0.42)	(0.51)
Registration ads	0.02	0.01	0.01	−0.13
	(0.07)	(0.06)	(0.05)	(0.59)
Postcode sector size medium1		−0.75***	−0.78***	−0.78***
		(0.09)	(0.09)	(0.09)
Postcode sector size medium2		−0.37***	−0.39***	−0.39***
		(0.10)	(0.10)	(0.10)
Postcode sector size small		−1.45***	−1.26***	−1.26***
		(0.09)	(0.09)	(0.09)
Mean age			−0.03*	−0.03*
			(0.01)	(0.01)
Missing covariate data			−0.54***	−0.58***
			(0.09)	(0.11)
University educated			−0.25	−0.25
			(0.27)	(0.27)
BAME			−0.08	−0.08
			(0.16)	(0.16)
Low density			−0.16	−0.16
			(0.09)	(0.09)
Registrations ads: Mean age				0.00
				(0.02)
Registrations ads: Missing covariate data				0.09
				(0.11)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.08	0.34	0.37	0.37
Adj. R^2	0.04	0.31	0.34	0.34
Num. obs.	879	879	879	879
RMSE	0.97	0.82	0.80	0.80

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A7: All registrations (Logged DV)

	(1)	(2)	(3)	(4)
(Intercept)	6.30^{***}	7.99^{***}	10.49^{***}	11.35^{***}
	(0.61)	(0.61)	(1.23)	(1.46)
Registration ads	0.11	0.08	0.03	−1.79
	(0.22)	(0.19)	(0.17)	(1.68)
Postcode sector size medium1		-0.74^{**}	-0.89^{***}	-0.90^{***}
		(0.25)	(0.24)	(0.25)
Postcode sector size medium2		−0.12	−0.26	−0.26
		(0.26)	(0.25)	(0.25)
Postcode sector size small		-4.56^{***}	-3.14^{***}	-3.14^{***}
		(0.29)	(0.29)	(0.30)
Mean age			−0.05	−0.07
			(0.03)	(0.04)
Missing covariate data			-3.56^{***}	-3.60^{***}
			(0.36)	(0.43)
University educated			−1.09	−1.06
			(0.87)	(0.87)
BAME			0.19	0.15
			(0.50)	(0.50)
Low density			−0.18	−0.17
			(0.26)	(0.26)
Registration ads: Mean age				0.05
				(0.04)
Registration ads: Missing covariate data				0.10
				(0.48)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.08	0.36	0.47	0.47
Adj. R^2	0.04	0.33	0.44	0.44
Num. obs.	879	879	879	879
RMSE	3.30	2.75	2.51	2.52

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

B.1.2 Young voters

Table A8 shows full regression tables when missing sectors are included for young people only. Table A10 demonstrates results with a standardized dependent variable and Table A9 shows results with a logged dependent variable for young people only.

Table A8: Young voter registrations (Including missing sectors)

	(1)	(2)	(2)	(4)
(Intercept)	200.02***	354.41***	540.60***	600.83***
	(41.86)	(41.24)	(104.06)	(125.78)
Registration ads	−3.46	−5.09	−6.54	−133.07
	(15.57)	(13.61)	(13.30)	(140.25)
Postcode sector size medium1		−162.65***	−168.11***	−168.11***
		(22.98)	(22.74)	(22.81)
Postcode sector size medium2		−83.34***	−87.28***	−87.51***
		(24.10)	(23.97)	(23.98)
Postcode sector size small		−316.87***	−269.32***	−269.90***
		(21.47)	(22.28)	(22.32)
Mean age			−3.12	−4.60
			(2.43)	(3.04)
Missing covariate data			−96.49***	−103.20***
			(18.72)	(24.18)
University educated			−148.17*	−146.57*
			(61.84)	(62.10)
BAME			30.66	27.84
			(40.45)	(40.05)
Low density			−23.00	−22.60
			(23.85)	(23.85)
Registration ads: Mean age				3.19
				(3.56)
Registration ads: Missing covariate data				13.81
				(28.24)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.14	0.35	0.37	0.37
Adj. R^2	0.10	0.31	0.34	0.33
Num. obs.	879	879	879	879
RMSE	230.56	201.62	198.08	198.20

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A9: Young voter registrations (Logged DV)

	(1)	(2)	(3)	(4)
(Intercept)	3.93***	5.16***	6.99***	7.80***
	(0.48)	(0.49)	(0.98)	(1.18)
Registration ads	0.08	0.06	0.02	−1.67
	(0.16)	(0.14)	(0.13)	(1.30)
Postcode sector size medium1		−0.61**	−0.72***	−0.72***
		(0.20)	(0.20)	(0.20)
Postcode sector size medium2		−0.08	−0.17	−0.17
		(0.20)	(0.20)	(0.20)
Postcode sector size small		−3.27***	−2.32***	−2.33***
		(0.21)	(0.23)	(0.23)
Mean age			−0.03	−0.05
			(0.02)	(0.03)
Missing covariate data			−2.13***	−2.21***
			(0.23)	(0.28)
University educated			−1.19	−1.17
			(0.63)	(0.63)
BAME			0.28	0.24
			(0.38)	(0.38)
Low density			−0.28	−0.27
			(0.20)	(0.20)
Registration ads: Mean age				0.04
				(0.03)
Registration ads: Missing covariate data				0.17
				(0.33)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.09	0.36	0.44	0.44
Adj. R^2	0.05	0.32	0.41	0.41
Num. obs.	879	879	879	879
RMSE	2.42	2.04	1.91	1.91

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A10: Young voter registrations (Standardized DV)

	(1)	(2)	(3)	(4)
(Intercept)	−0.15	0.46**	1.20**	1.44**
	(0.17)	(0.16)	(0.41)	(0.50)
Registration ads	−0.01	−0.02	−0.03	−0.53
	(0.06)	(0.05)	(0.05)	(0.55)
Postcode sector size medium1		−0.64***	−0.66***	−0.66***
		(0.09)	(0.09)	(0.09)
Postcode sector size medium2		−0.33***	−0.34***	−0.35***
		(0.10)	(0.09)	(0.09)
Postcode sector size small		−1.25***	−1.06***	−1.07***
		(0.08)	(0.09)	(0.09)
Mean age			−0.01	−0.02
			(0.01)	(0.01)
Missing covariate data			−0.38***	−0.41***
			(0.07)	(0.10)
University educated			−0.59*	−0.58*
			(0.24)	(0.25)
BAME			0.12	0.11
			(0.16)	(0.16)
Low density			−0.09	−0.09
			(0.09)	(0.09)
Registration ads: Mean age				0.01
				(0.01)
Registration ads: Missing covariate data				0.05
				(0.11)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.14	0.35	0.37	0.37
Adj. R^2	0.10	0.31	0.34	0.33
Num. obs.	879	879	879	879
RMSE	0.91	0.80	0.78	0.78

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C Robustness Checks

In Table A11, we replicate our analysis with a population-standardised dependent variable (excluding missing sectors). To standardise the dependent variable by population, we divide the number of registered voters by the number of all residents older than 18 years old at the postcode sector level. In Table A13, we show this analysis for young people, where we divide the number of registered voters by number of young residents between the age of 18 and 35 at the postcode sector level (excluding missing sectors). In both, we exclude those sectors that the standardised dependent variable did not vary between 0 and 1. We believe this discrepancy may be due to student populations registering at home even though they moved out. A large portion of those excluded sectors are from Scotland. In Figure A3, we show mean plots with 95% CI where the dependent variable varies between 0 and 1. In Tables A12 (all people) and A14 (young people), we replicate this analysis by including missing sectors and assigning 1 when the number of registered voters is higher than the residents in that postcode sector. Our null results are robust to both specifications.

C.1 Population-standardised dependent variable

Table A11: Standardised registration for all people at postcode sector sector level (by 2019 estimates) (Excluding missing sectors) (Register data)

	(1)	(2)	(3)	(4)
(Intercept)	0.4824**	0.4824**	0.6833*	0.8347*
	(0.1463)	(0.1463)	(0.2847)	(0.3427)
Registration ads	0.0138	0.0138	0.0187	−0.2998
	(0.0301)	(0.0301)	(0.0300)	(0.3292)
Mean age			−0.0032	−0.0070
			(0.0068)	(0.0083)
Low density			−0.0588	−0.0581
			(0.0533)	(0.0531)
Postcode sector size medium1			−0.0426	−0.0425
			(0.0427)	(0.0428)
Postcode sector size medium2			0.0239	0.0227
			(0.0405)	(0.0403)
Postcode sector size small			−0.0434	−0.0455
			(0.0594)	(0.0597)
Registration ads: Mean age				0.0080
				(0.0084)
R^2	0.0895	0.0895	0.1011	0.1030
Adj. R^2	0.0149	0.0149	0.0173	0.0174
Num. obs.	529	529	529	529
RMSE	0.3396	0.3396	0.3392	0.3392

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A12: Standardised registration for all people at postcode sector level (by 2019 estimates) (Including missing sectors)(Register data)

	(1)	(2)	(3)	(4)
(Intercept)	0.7883***	0.7883***	0.6487**	0.6923*
	(0.0802)	(0.0802)	(0.2277)	(0.2793)
Registration ads	0.0082	0.0082	0.0116	−0.0819
	(0.0268)	(0.0268)	(0.0266)	(0.2790)
Mean age			0.0056	0.0045
			(0.0056)	(0.0068)
Low density			−0.0987*	−0.0986*
			(0.0492)	(0.0492)
Postcode sector size medium1			−0.0152	−0.0149
			(0.0383)	(0.0384)
Postcode sector size medium2			0.0317	0.0315
			(0.0356)	(0.0356)
Postcode sector size small			−0.0234	−0.0234
			(0.0510)	(0.0511)
Registration ads: Mean age				0.0023
				(0.0070)
R^2	0.1104	0.1104	0.1200	0.1202
Adj. R^2	0.0563	0.0563	0.0593	0.0580
Num. obs.	698	698	698	698
RMSE	0.3495	0.3495	0.3490	0.3492

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A13: Standardised registration for young people at postcode sector level (by 2019 estimates) (Excluding missing sectors) (Register data)

	(1)	(2)	(3)	(4)
(Intercept)	0.1398	0.1398	−0.1993*	−0.1149
	(0.0694)	(0.0694)	(0.0941)	(0.1146)
Registration ads	0.0097	0.0097	0.0099	−0.1546
	(0.0094)	(0.0094)	(0.0092)	(0.1045)
Mean age			0.0085***	0.0064*
			(0.0022)	(0.0027)
Low density			−0.0085	−0.0078
			(0.0171)	(0.0170)
Postcode sector size medium1			−0.0047	−0.0045
			(0.0126)	(0.0126)
Postcode sector size medium2			0.0048	0.0043
			(0.0118)	(0.0118)
Postcode sector size small			0.0181	0.0174
			(0.0191)	(0.0193)
Registration ads: Mean age				0.0041
				(0.0027)
R^2	0.2633	0.2633	0.3008	0.3053
Adj. R^2	0.1992	0.1992	0.2316	0.2349
Num. obs.	501	501	501	501
RMSE	0.1035	0.1035	0.1014	0.1012
N Clusters	501	501	501	501

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A14: Standardised registration for young people at postcode sector level (by 2019 estimates) (Including missing sectors) (Register data)

	(1)	(2)	(3)	(4)
(Intercept)	0.3504***	0.3504***	−0.2889*	−0.3429*
	(0.0745)	(0.0745)	(0.1213)	(0.1499)
Registration ads	−0.0101	−0.0101	−0.0080	0.1079
	(0.0134)	(0.0134)	(0.0129)	(0.1349)
Mean age			0.0162***	0.0175***
			(0.0030)	(0.0038)
Low density			−0.0355	−0.0356
			(0.0194)	(0.0194)
Postcode sector size medium1			0.0412*	0.0409*
			(0.0187)	(0.0187)
Postcode sector size medium2			0.0383*	0.0386*
			(0.0169)	(0.0169)
Postcode sector size small			0.0282	0.0282
			(0.0269)	(0.0268)
Registration ads: Mean age				−0.0029
				(0.0035)
R^2	0.3413	0.3413	0.3855	0.3862
Adj. R^2	0.3011	0.3011	0.3431	0.3428
Num. obs.	698	698	698	698
RMSE	0.1765	0.1765	0.1711	0.1711

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

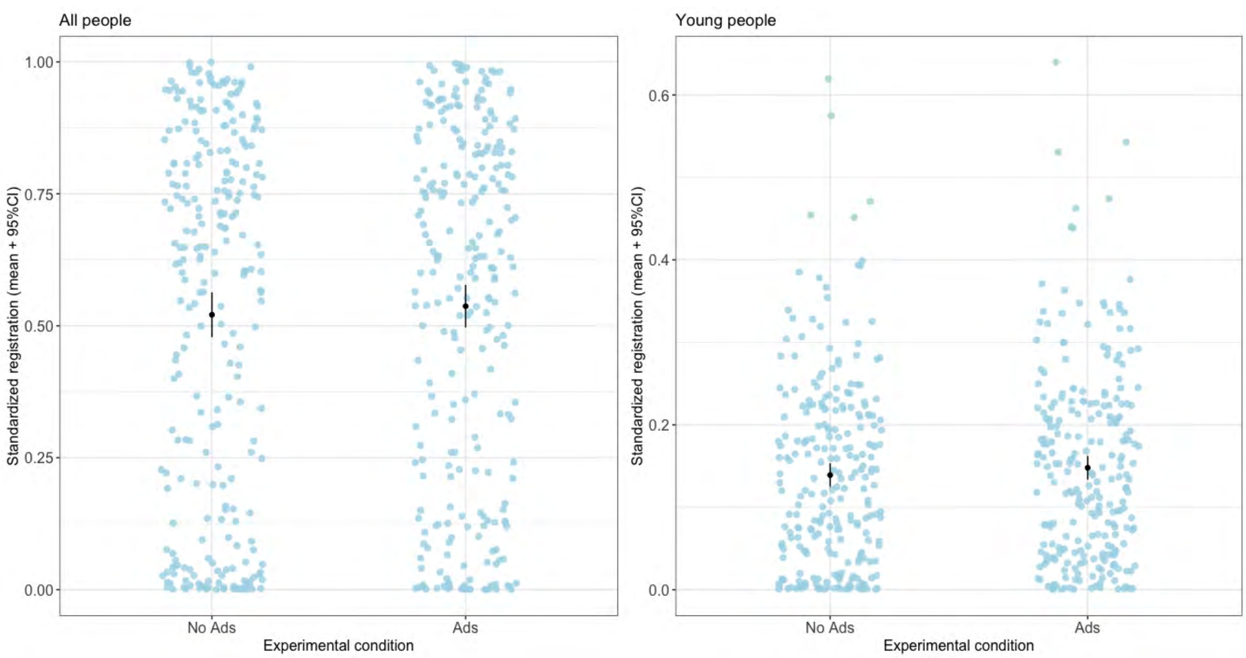


Figure A3: Population standardised mean plots with 95% CI; (N = *529*).

C.2 Interaction with Mobility (Density)

Table A15 reports interaction results with with population density at the postcode sector.

Table A15: All registrations (with density interaction)

	(1)	(2)	(3)	(4)
(Intercept)	2255.81***	4741.01***	8430.02***	8368.51***
	(498.61)	(498.84)	(1272.65)	(1281.14)
Registration ads	62.90	39.16	18.49	171.05
	(198.28)	(168.21)	(164.67)	(320.41)
Low density	541.12*	32.07	−484.69	−309.87
	(247.96)	(207.16)	(262.82)	(337.07)
Postcode sector size medium1		−2290.18***	−2385.12***	−2388.68***
		(287.76)	(284.81)	(285.33)
Postcode sector size medium2		−1126.37***	−1193.86***	−1194.01***
		(298.11)	(295.38)	(295.24)
Postcode sector size small		−4427.04***	−3827.26***	−3834.07***
		(271.77)	(274.93)	(274.79)
Mean age			−76.24*	−76.82*
			(30.19)	(30.20)
Missing covariate data			−1637.42***	−1676.55***
			(276.87)	(363.94)
University educated			−761.33	−778.62
			(811.28)	(811.43)
BAME			−229.80	−220.66
			(487.75)	(488.65)
Registration ads: Low density				−342.76
				(396.71)
Registration ads: Missing covariate data				103.55
				(408.94)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.09	0.34	0.37	0.37
Adj. R^2	0.04	0.31	0.34	0.34
Num. obs.	879	879	879	879
RMSE	2940.83	2495.55	2444.46	2445.50

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.3 Interaction with 2017 Advertisement Spending

Table A16 reports interaction results with all candidates' combined ad spending in the preceding 2017 General Election.

Table A16: All registrations (with advertising interaction)

	(1)	(2)	(3)	(4)
(Intercept)	3242.11***	5156.34***	8456.22***	8430.21***
	(180.92)	(282.10)	(1232.55)	(1234.18)
Registration ads	65.17	43.12	26.45	126.14
	(202.73)	(171.44)	(167.50)	(238.33)
Low advertising	−69.67	−72.66	−113.97	−16.77
	(202.92)	(171.41)	(171.63)	(244.65)
Postcode sector size medium1		−2230.22***	−2383.99***	−2380.47***
		(284.86)	(283.06)	(283.63)
Postcode sector size medium2		−1004.86***	−1125.47***	−1122.60***
		(300.91)	(297.48)	(297.37)
Postcode sector size small		−4327.33***	−3776.59***	−3774.65***
		(261.42)	(272.95)	(273.56)
Mean age			−68.10*	−68.96*
			(29.16)	(29.31)
Missing covariate data			−1576.76***	−1566.36***
			(264.14)	(266.03)
University educated			−670.85	−658.41
			(670.10)	(671.58)
BAME			44.30	40.72
			(380.25)	(380.03)
Low density			−467.52	−459.68
			(241.14)	(242.49)
Registration ads: Low advertising				−196.32
				(338.05)
Fixed effects	No	No	No	No
R^2	0.00	0.29	0.33	0.33
Adj. R^2	-0.00	0.28	0.32	0.32
Num. obs.	879	879	879	879
RMSE	3005.76	2541.41	2479.80	2480.74

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.4 Analysis At the Postcode Level

C.4.1 All voters

Table A17 shows regression results at the postcode level. The first column shows results with missing sectors excluded, the second column shows results with missing sectors included and the third column shows results with a logged dependent variable. Table A18 reports the full regression table with covariates at the postcode level. Standard errors are clustered at the level of assignment, the postcode sector.

Table A17: All registrations at postcode level

	(1): n with NA	(2): n with imputed 0s	(3): logged n
(Intercept)	27.39***	15.09***	1.67***
	(1.01)	(2.54)	(0.27)
Registration ads	0.04	0.48	0.06
	(0.49)	(0.96)	(0.09)
Fixed effects	Yes	Yes	Yes
R^2	0.06	0.03	0.04
Adj. R^2	0.06	0.03	0.04
Num. obs.	90678	149240	149240
RMSE	24.30	24.51	1.65
N Clusters	717	878	878

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A18: All registrations at postcode level (Including missing sectors)

	(1)	(2)	(3)
(Intercept)	15.09***	51.42***	56.38***
	(2.54)	(7.47)	(9.16)
Registration ads	0.48	0.60	−10.84
	(0.96)	(0.94)	(11.83)
Mean age		−0.72***	−0.83***
		(0.16)	(0.20)
Missing covariate data		4.30*	3.94
		(2.08)	(2.33)
University educated		−7.12	−7.32
		(6.61)	(6.67)
BAME		−17.85**	−17.85**
		(6.34)	(6.32)
Low density		−8.02***	−8.02***
		(1.38)	(1.38)
Registration ads: Mean age			0.27
			(0.30)
Registration ads: Missing covariate data			0.50
			(2.08)
Fixed effects	Yes	Yes	Yes
R^2	0.03	0.04	0.04
Adj. R^2	0.03	0.04	0.04
Num. obs.	149240	149240	149240
RMSE	24.51	24.38	24.37
N Clusters	878	878	878

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.4.2 Young voters

Table A19 shows regression results at the postcode level for young people only. The first column shows results with missing sectors excluded, the second column shows results with missing sectors included and the third column shows results with a logged dependent variable. Table A20 displays the full regression table with covariates at the postcode level for young people only. Standard errors are clustered at the level of assignment, the postcode sector.

Table A19: Young voter registrations at postcode level

	(1): n with NA	(2): n with imputed 0s	(3): logged n
(Intercept)	3.60^{***}	1.16^{***}	0.43^{***}
	(0.17)	(0.23)	(0.08)
Registration ads	−0.10	−0.01	0.00
	(0.06)	(0.08)	(0.03)
Fixed effects	Yes	Yes	Yes
R^2	0.06	0.03	0.04
Adj. R^2	0.06	0.03	0.04
Num. obs.	56074	149240	149240
RMSE	3.09	2.60	0.74
N Clusters	684	878	878

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A20: Young voter registrations at postcode level (Including missing sectors)

	(1)	(2)	(3)
(Intercept)	1.16^{***}	3.34^{***}	3.79^{***}
	(0.23)	(0.55)	(0.64)
Registration ads	−0.01	−0.01	−1.02
	(0.08)	(0.08)	(0.84)
Mean age		-0.04^{***}	-0.05^{***}
		(0.01)	(0.01)
Missing covariate data		0.29	0.29
		(0.15)	(0.17)
University educated		-1.48^{**}	-1.50^{**}
		(0.46)	(0.46)
BAME		−0.39	−0.40
		(0.49)	(0.48)
Low density		-0.44^{***}	-0.45^{***}
		(0.10)	(0.10)
Registration ads: Mean age			0.03
			(0.02)
Registration ads: Missing covariate data			−0.03
			(0.15)
Fixed effects	Yes	Yes	Yes
R^2	0.03	0.04	0.04
Adj. R^2	0.03	0.04	0.04
Num. obs.	149240	149240	149240
RMSE	2.60	2.60	2.60
N Clusters	878	878	878

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.5 Complier Average Causal Effect (CACE)

Table A21: 2SLS regression with successful ad placement as endogeneous variable

	(1)	(2)
Successful ad placement	69.24	20.59
	(219.75)	(183.31)
Postcode sector size medium1		-2385.17^{***}
		(284.80)
Postcode sector size medium2		-1194.07^{***}
		(295.36)
Postcode sector size small		-3825.26^{***}
		(275.57)
Mean age		-76.24^{*}
		(30.19)
University educated		-762.12
		(811.51)
BAME		-229.82
		(487.72)
Low density		-485.01
		(262.69)
Missing covariate data		-1632.94^{***}
		(280.98)
Fixed effects	Yes	Yes
R^2	0.08	0.37
Adj. R^2	0.04	0.34
Num. obs.	879	879
RMSE	2944.10	2444.27

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

42 out of 394 postcode sector assigned to treatment could not be successfully targeted on digital platforms. This is a case of one-sided non-compliance and can be estimated via 2SLS. In Table A21 we use this ad placement success indicator as a compliance measure and run a 2SLS regression with assignment to treatment as the exogenous variable and whether the ad was successfully placed as the endogenous variable. The results of this IV specification are reported in Table A21. Since the CACE is defined as the ITT divided by the compliance rate, the estimated CACEs are just slightly larger than the ITTs reported in Table A3.

D Covariate Data Visuals

Figure A4: Mean age by Constituency ($N = 40$)

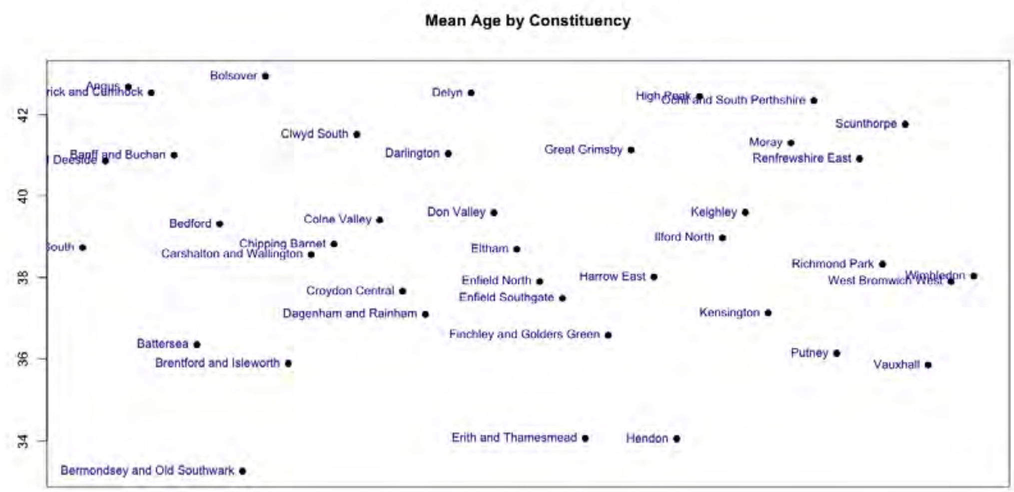


Figure A5: University Education by Constituency ($N = 40$)

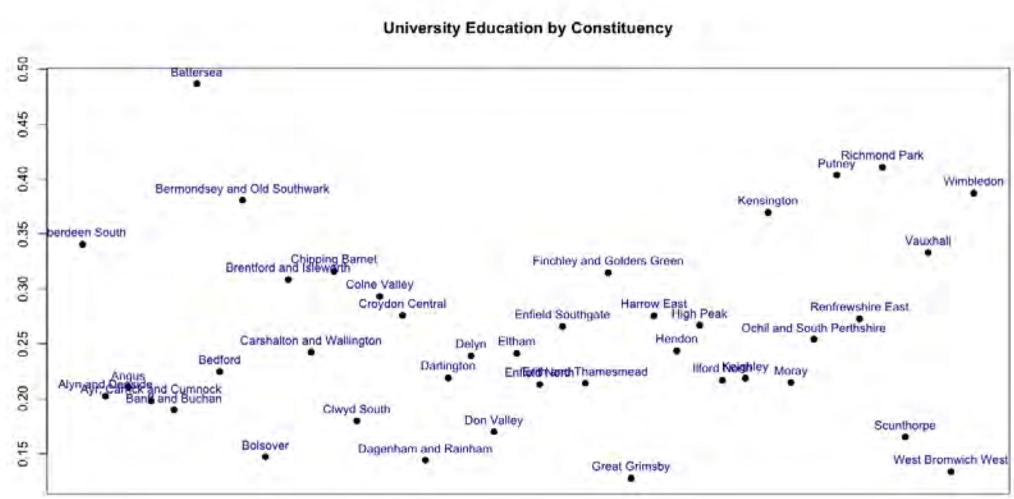


Figure A6: Population Density by Constituency ($N = 40$)

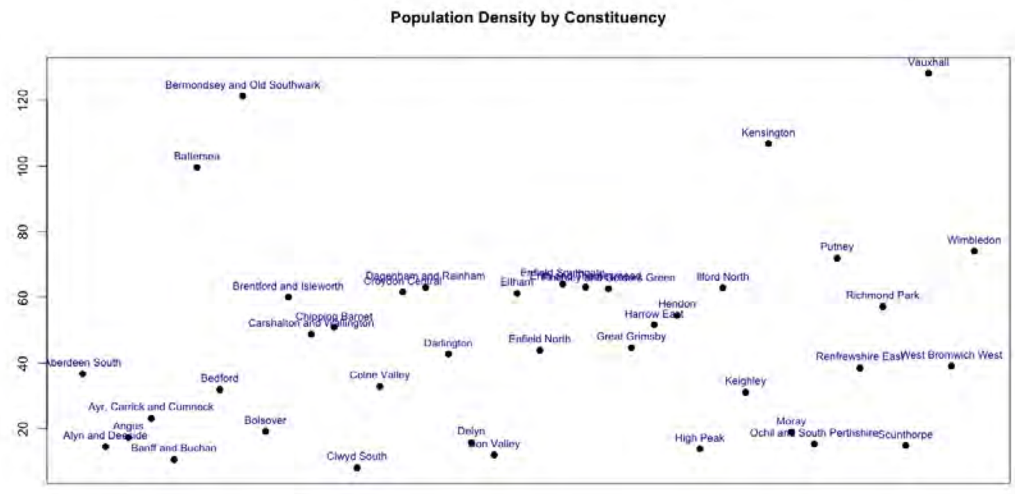
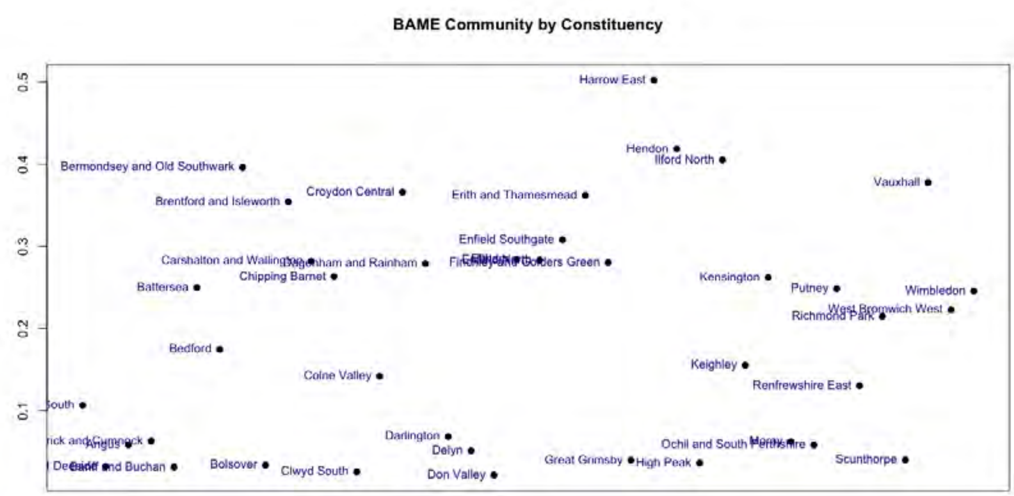


Figure A7: BAME Community by Constituency ($N = 40$)



E Deviations from the Pre-Analysis Plan

The Pre-Analysis Plan for this study is available via https://osf.io/fyxsd/. In what follows we outline and explain any deviations from the Pre-Analysis Plan.

E.1 Levels of outcome measurement

We pre-registered that we would define the outcome variable as the absolute number of registrations per household, and as the absolute number of registrations per polling district. As anticipated in the PAP, due to data protection concerns, we were unable to obtain outcome data at the household level. Moreover, while we were able to obtain outcome data at the polling district level, polling districts are not perfectly nested within postcode sectors, the unit of assignment. We failed to identify this issue in advance. Since single polling districts often cross multiple postcode sectors, the same polling district would be assigned to multiple experimental conditions at once, and therefore results would mechanically be biased towards zero. We therefore decided to record the outcome at the level of assignment, the 4-digit postcode sector, and at the smallest level of aggregation that was perfectly nested within the postcode sector, the 6 digit postcode.

E.2 Secondary outcome variable: Turnout

As pre-registered, we also intended to test if Get-Out-The-Vote reminders assigned via a factorial design and sent via Instagram and Snapchat 2-3 days before the election, amplified the Voter Registration ads' effect on turnout, but we were unable to obtain validated voter turnout data for 37 out of 40 constituencies. Since the GOTV messages were all sent after the voter registration deadline, the voter registration outcomes reported in this paper could not have been influenced by GOTV ads. Since the effects of the voter registration ads on voter registrations are null, our best guess is that any downstream effects on turnout will also have been null.

E.3 Inclusion of Census Covariates

As pre-registered, we intended to use voter registration in the 2017 UK General Election for covariate-adjustment, but we were unable to obtain the 2017 registers. We anticipated that this might happen in the PAP. To gain statistical power via covariate-adjustment, we instead use 2011 Census covariates as a second best option. We did not pre-register the Census covariates because we did not think about the possibility of matching the 2011 Census to treatment assignment via place identifiers. Covariate-adjustment improves precision, but as would be expected given random assignment, point estimates are similar.