Could rainfall have swung the result of the Brexit referendum?

Patrick A. Leslie[a]* and Barış Arı[b]

[a] *Centre for Social Research and Methods, Australian National University, Australia*

[b] *Department of Government, University of Essex, UK*

* Corresponding author. E-mail address: patrick.leslie@anu.edu.au (P.A. Leslie).

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Abstract

Previous studies have shown that weather conditions may affect voter turnout, sometimes in ways that could plausibly swing the result of a close election. On the day of Britain's EU Referendum, the presence of torrential rain in the South-East of England and Northern Ireland raised concern in the media that voter turnout could be affected in a manner that favoured the Vote Leave campaign. To test this assertion, this paper takes data at the polling district level and overlays interpolated rainfall data using geographic information system (GIS) technology. Despite widespread expectations to the contrary, our analysis shows that the rain had the greatest effect on the leave vote, reducing the Brexiteer tally by as many as 4,618 votes in one district. We find that if the referendum had taken place on a sunny day, there would have been a small increase in the margin of victory for Vote Leave.

1 Introduction

Torrential rainfall on the day of the Brexit referendum severely affected parts of the United Kingdom, particularly South East England, London and Northern Ireland. The Met Office issued an amber warning and the London Fire Brigade reported that it had responded to more than 400 incidents, including rescuing residents by boats (London Fire Brigade, 2016). The BBC published images of water "up to six inches deep" at polling stations (BBC News, 2016a) as reports emerged throughout the day that several referendum polling stations had closed because of flooding (Smith, 2016) and that rainfall had caused severe damage to property in the Kent districts of Canterbury, Swale and Thanet (ESWD, 2017). As a result of extensive rail disruption, thousands of commuters were stuck at central train stations across London before the polls were closed. Most notably, Waterloo train station in London, which serves up to 250,000 passengers per day, was closed after rainfall threw services into chaos (Tran, 2016). The severity of rain on polling day caused media reports to question whether the weather could affect the turnout of the referendum (Knapton, 2016; Aron, 2016). Following press speculation and several studies of the electoral effects of rainfall,[1] we address the question: could rainfall have changed the result of the UK's EU referendum?

In this study we use fine-grained radar data on rainfall between 6 am and 10 pm on 23rd June 2016, a measurement window that allows us to measure the effect of rainfall just before and during voting hours (7 am to 10 pm). Rainfall was highly variable across the UK with much of the day's rain concentrated around London the South-East, Northern Ireland and parts of western Scotland, all areas that predominantly supported remain. The district of Hartsmere, some 15 miles north of London, experienced the heaviest downpour with 22 mm of rain over the 16 hour period, nearly half the total expected rainfall in June of around 50 mm (Met Office, 2016).[2]

The distribution of rainfall on polling day warrants proper investigation of the intriguing question posed originally by media commentary, but also poses sizeable challenges to estimate the effect of rainfall

[1] See Gomez et al. (2007), Persson et al. (2014), Eisinga et al. (2011), Knack (1994), Horiuchi and Kang (2017), Bassi and Williams (2017), Fraga and Hersh (2011), and Gatrell and Bierly (2002)

[2] Rainfall over the 24 hour period showed even greater extremes, with 50 mm (roughly 2 inches) or more experienced by 8 London Boroughs.

at the district level and to assess its effect on the referendum result itself. We employ techniques developed to accurately model compositional electoral data (Tomz et al., 2002). We leverage recent innovations in statistical analysis (Fong et al., 2017; Imai and Ratkovic, 2014) to improve balance on pretreatment covariates – a problem caused by the lopsided distribution of rainfall. We also use post-estimation techniques that allow us to determine the effect of rainfall on vote share through both differential turnout and by the recently defined 'vote-shift' channel (Horiuchi and Kang, 2017), by which rainfall causes undecided voters to change their mind through its effect on mood.

Our findings suggest that rainfall had a statistically significant but substantively inconsequential effect on the referendum. Our estimated rainfall effect is slightly in excess of existing estimations in the literature. More interestingly, we find that rainfall affected the leave vote more acutely than remain. This result refutes the conventional wisdom that leave supporters were more committed than remain supporters. Indeed, Nigel Farage – UK Independence Party (Ukip) leader and persistent campaigner to leave the EU – claimed that his voters would "crawl over broken glass" to vote for Brexit (BBC News, 2016b). Despite this, we find that a counterfactual election day in which no rain fell would have produced a slightly altered but much the same substantive result – a win for Vote Leave by a margin exceeding 1 million votes.

2 Rainfall, Elections and the EU Referendum

Rainfall is among a set of variables commonly believed to affect the propensity to vote through its impact on the cost of voting as described in the rational voter model (Merrifield, 1993; Downs, 1957; Riker and Ordeshook, 1968). Accordingly, dedicated studies of rainfall and elections generally find a negative effect on turnout, but the extent to which rainfall substantively changes election results is far less certain. Eisinga et al. (2011) measure the effect of rainfall in the Dutch context between 1971-2010 and find that 25 mm of rainfall is indicative of a 1.02% percentage point decrease in the level of voter turnout. In the case of the United states, Gomez et al. (2007) find that an inch of rainfall decreases turnout by 0.98%, Horiuchi and Kang find a turnout decrease of 1.16% for every inch of rainfall and Gatrell and Bierly (2002) find that rainfall depressed turnout in Kentucky Primary elections. However, Persson et al. (2014) integrate the posited costs of high rainfall into the rational voter model and find that rainfall had no substantive negative effect on turnout in Swedish elections between 1976-2010.

The discrepancy in findings is likely due to a number of factors, notwithstanding considerable variation in data collection and measurement. Firstly, voter characteristics may contribute to heterogenous treatment effects. Studies of differential turnout argue that differences in voter commitment between US political parties condition how damaging rainfall is to voter turnout in each political group (Gomez et al., 2007; Horiuchi and Kang, 2017). According to Gomez et al., “bad weather may be the last straw for peripheral voters, and according to the conventional wisdom, these voters may be disproportionately inclined to support the Democratic presidential candidate” (Gomez et al., 2007, p. 658). Similarly, Knack (1994) finds that the negative effect of rainfall on turnout is limited to voters with low levels of civic duty, contributing to the expectation that parties relying on such voters in greater numbers will be more susceptible to the effect of inclement weather.

Secondly, electoral systems and circumstances appear to matter. Where systems are proportional and political participation is high (Persson et al., 2014), the cost of voting is lower than in other systems, since votes are less likely to be redundant than in single member districts. In such cases, voters are less likely to conclude that the discomfort caused by a walk in the rain is futile. In single member district systems, voters may only feel the same level of motivation in districts where the election race is considered close (Fraga and Hersh, 2011; Shachar and Nalebuff, 1999), diminishing the effect of rainfall in marginal districts. Thus, in typical single member district elections, rainfall may have a significant effect on vote share in safe districts without affecting the results for tightly contested seats.

Recently, researchers have extended the analysis of weather events beyond the differential turnout hypothesis to suggest that rainfall may also systematically affect the vote choice of undecided and moderate voters (Bassi and Williams, 2017; Horiuchi and Kang, 2017). The conjecture is that inclement weather affects mood, which according to the predictions of prospect theory (Kahneman and Tversky, 2013) affects risk aversion, resulting in a vote-shift towards candidates seen as the least risky option. Where political options are considered distinct in terms of risk – as is the case in the USA where Democrat candidates are considered the riskier option (Kam and Simas, 2010) – estimates of a vote-shift channel of the rainfall effect are estimated to account for at least two thirds of the Republican rainfall advantage (Kam and Simas, 2010).

The literature on euroscepticism in Britain provides important information on the demographic structure and political motivation on the Vote Leave campaign, and so sheds light on expectations for differential turnout. On the one hand, the EU referendum provided the British electorate a vote on an issue substantially different from general elections. Some reports suggested that Vote Leave may have stood to profit from decreased turnout, since it was claimed that Brexiteers had arguably more strongly held beliefs vis-a-vis the European Union and would therefore be more enthused about the prospect of voting (Twyman, 2016; Dunford and Kirk, 2016). Some of this dedication was reflected in the reportage of the referendum itself, with pro-leave voters urging each other to mark ballots with pen instead of the pencils provided in the belief that corrupt election officials would attempt to re-assign pencil marked ballots (Griffin, 2016). If, as discourse suggests, pro-leave voters were more dedicated to their cause, then adverse weather conditions may have given an advantage to the Vote Leave campaign.

However Ford and Goodwin (2014, p. 152) note that the demographic support for Ukip (the pro-Brexit party) is “anchored in a clear social base: older blue-collar voters, citizens with few qualifications, whites and men”. Low education and social class are typically associated with reduced political engagement in Britain (Hansard Society, 2017) and in other advanced industrial economies (Lijphart, 1997; Gallego, 2010; Kasara and Suryanarayan, 2015), but were strong predictors of Brexit support in the lead-in to the referendum (Twyman, 2016). Studies have shown that once people have become accustomed to voting regularly, they are less likely to be deterred by factors such as rainfall impacting upon their decision to vote (Aldrich et al., 2011; Gerber et al., 2003). The relative lack of voting habit among important demographics of the pro-Brexit support shows a greater susceptibility of the leave vote to differential turnout in rainy conditions.

Another factor that may indicate a negative effect of rainfall on differential turnout is that older and poorer voters are potentially more likely to be physically deterred by poor weather for reasons of safety or reliance on public transport or walking (Knack, 1994; Eisinga et al., 2011; Gomez et al., 2007, p. 191), though there is little conclusive evidence for this in statistical analysis. Nevertheless, the theoretical expectation remains that the preponderance of older voters in the pro-Brexit camp could have lead to a differential turnout caused by a deterrent effect of rainfall on the elderly.

With regard to vote-shift (where marginal voters change their vote choice due to rainfall), the expected direction of effect is clear. Remain, as the least risky *status quo* option (Harries, 2016; Clarke et al., 2017, p. 4), should have a significant advantage over undecided voters in rainy conditions (Bassi and Williams, 2017; Horiuchi and Kang, 2017). This expectation is magnified by the parallel expectation that the high issue salience of the referendum should have reduced the effect of rainfall on turnout (Persson et al., 2014). The combination of these expectations is that rainfall may affect the vote share of leave and remain more than it affects turnout. In such a situation, differential turnout cannot account for the entire effect of rainfall on vote share and therefore vote-shift must logically account for some of the difference. In this case we expect vote-shift to benefit the remain vote share – i.e. we expect marginal voters to switch their vote choice from leave to remain because of the poor weather.

We form three hypotheses linking rainfall to the UK’s EU referendum result. Our first hypothesis follows the literature on rainfall and elections (**H1:** rainfall reduces referendum turnout).

Our theoretical expectations for vote share are split into two subcategories: differential turnout and vote-shift. Theoretical expectations of the effect of rainfall on differential turnout are in conflict – on the one hand, media commentary on the referendum indicated that issue salience and voter commitment was stronger among leave supporters (**H2a:** rainfall reduces the remain vote more acutely than the leave vote). On the other hand remain supporters were more likely to have formed voting habits, and were less likely to be physically deterred from voting by rainfall. We therefore set a competing hypothesis

(**H2b:** rainfall reduces the leave vote more acutely than the remain vote).

Conversely, our theoretical expectation for the vote-shift channel is clear, as choosing to remain in the EU was considered the least risky option (**H3:** rainfall causes voters to change vote choice from leave to remain).

3 Analysis

In the following section, we describe the data collection process and discuss balancing on pre-treatment covariates. We start our estimation using OLS on turnout and leave share separately. Next, we run Seemingly Unrelated Regression (SUR) models on compositional electoral data. These models allow us to estimate the impact of rainfall on both turnout and vote share jointly. Based on these latter estimates, we then estimate the counterfactual referendum result on a day without rainfall, the extent to which the rainfall effect was caused by differential turnout or vote-shift, and the effect of postal voting on the rainfall effect. We conclude with a brief application to election forecasting, showing that the inclusion of rainfall significantly reduces forecasting errors of leave share in the EU Referendum.

3.1 Data

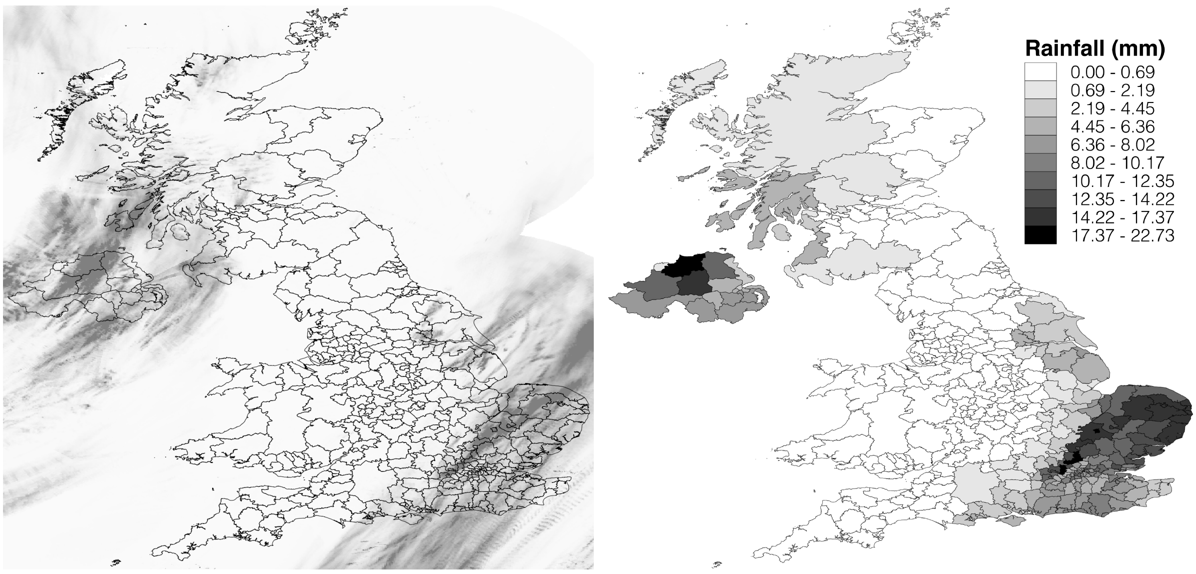

Figure 1: Rainfall between 06:00 am and 10:00 pm on 23 June 2016 using radar measurements and referendum counting districts

Our measurement of rainfall on 23 June 2016 relies on data from the Met Office's NIMROD System (Met Office, 2003; Thomas, 2015). The NIMROD System collects radar data for rainfall every five minutes at a resolution of 1 km^2. We then transformed the radar data to Environmental Systems

Research Institute (ESRI) ASCII raster format. In order to measure rainfall for the voting period, we limited the time period from 6 am and 10 pm (official voting hours were between 7 am and 10 pm), yielding 192 separate raster images extracted from the NIMROD radar data, which were then summed up to provide accurate measurements of rainfall within the period 6 am-10 pm. We also measured rainfall for the period 12 midnight to 10pm.[3] The vector polygons for referendum counting areas (seen in Figure 1) are taken from ESRI and are aggregated to the Local Authority Area for England, Scotland and Wales. These polygons did not originally include lower level divisions for Northern Ireland (nor indeed did the official election results according to the Electoral Commission). However, we were able to identify voting areas in Northern Ireland by constituency, as the BBC's Referendum coverage (BBC News, 2016c) included a constituency level breakdown of Northern Irish results. We took the BBC's Northern Ireland results and then georeferenced them to polygons for each of Northern Ireland's parliamentary constituencies, adding these polygons to our data.[4]

The referendum results data were available from the Electoral Commission (2017). As discussed above, additional results were taken from the BBC referendum results website. Majority remain areas were grouped around London and other significant urban areas such as Liverpool and Manchester. Scotland and Northern Ireland also voted in opposition to England and Wales with majority remain results for both nations. The majority of leave votes were spread through rural and suburban Britain. Two counting districts, Shetland and Orkney (pop. 45,000) and Gibraltar (pop. 32,000) were dropped from the analysis due to the lack of available rainfall data - both voted heavily in favour of remain. This is unlikely to affect the overall conclusion due to the small population size of both districts.

We then collected data for a number of covariates to create predictive models of turnout and vote-share. First, we created a measure of political engagement by including turnout from the previous General Election of 2015 (Figure 2, left). Due to the fact that the counting areas of the EU referendum and constituency boundaries of the 2015 general election do not correspond to one another, we adopted a zonal statistics approach to transform the 2015 election data to the referendum units. First, we transformed vector data for the 2015 elections to raster data. Then, we overlaid the referendum polygons onto this raster and used zonal statistics to calculate an average value for turnout in each referendum district. This solution was not necessary for Northern Ireland as the referendum polygons and 2015 parliamentary election constituencies are the same. We used the election data directly from the Electoral Commission for Northern Ireland. Figure 2 shows the levels of turnout in the 2015 general election and the EU referendum (national levels of turnout are 66.1% and 72.2% respectively). At the level, the two

[3]Alternative model estimations using the longer time window are included in the Appendix. Results do not substantively change our key findings.

[4]For simplicity, we refer to these referendum vote counting areas as 'districts', though we note that there is no such official designation.

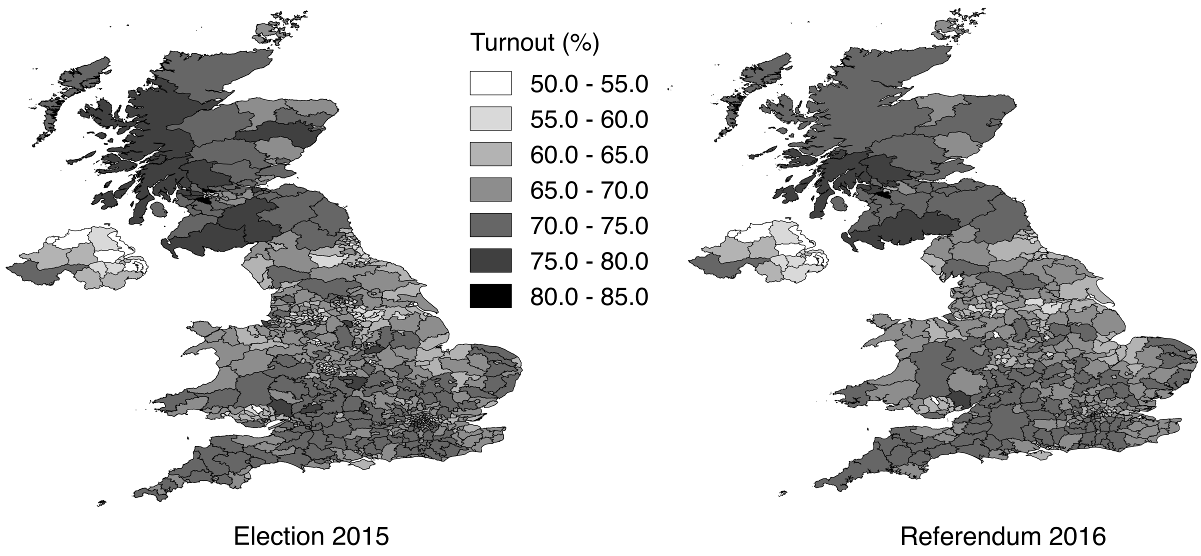

Figure 2: Turnout in the 2015 General Election (left) and the 2016 EU Referendum (right).

are positively correlated (0.68 Spearman correlation).

The vote share of Ukip in the 2014 European Parliamentary elections was also included (Electoral Commission, 2017) as a measure of underlying support for the leave vote. Due to Northern Ireland electing MEPs via a Single Transferable Vote system, electoral results report a single district for the whole of Northern Ireland (3.9%). In order to avoid under-reporting variance for the region, we allowed this vote share to vary by generating a truncated normal distribution with a minimum of zero, a maximum value and standard deviation equal to the Ukip's vote share in Scotland, whose overall reported vote share was similar. We iterated this distribution until the expected value for the Ukip vote share in Northern Ireland fell between 3.9%-3.95%, approximately the vote share that Ukip had achieved in Northern Ireland in that election.

We also included demographic variables from census data and official labour market statistics sources (Nomis, 2011; DfE, 2015) and from the Northern Ireland Statistics and Research Agency. Five demographic variables were collected including median age, gender balance, the percentage of residents with a first degree or equivalent, logged population density, and the percentage of residents with lower social grade. [5] Finally, we collected data measuring the level of postal voting during the referendum in order to test an ancillary hypothesis about the possible mediating influence of postal votes on the rainfall effect.

[5] Grades D and E, according to the classification of the Office for National Statistics (ONS, 2011)

3.2 Balancing on Pre-Treatment Covariates

One of the challenges to estimating the average treatment effect (ATE) from the data collected is the pre-treatment imbalance caused by the geographical distribution of rainfall across the country on polling day. As Figure 1 makes clear, rainfall was largely confined to the south eastern part of England, as well as the majority of Northern Ireland. This is an issue for inference because the correlation between rainfall and other important covariates could bias our estimates. Column 3 of Table 1 illustrates this issue. Rainfall has strong associations with median age, population density and social grade, indicating that rain fell more often on younger, poorer and more urbanised districts. In order to correct for this imbalance, we use non-parametric Covariate Balancing Generalised Propensity Scores (npCBGPS), developed as a means to solve imbalance problems with continuous treatment (Fong et al., 2017). The method works by varying observation weights in order to minimize the association between the treatment (rainfall) and other covariates.

When applied to the EU Referendum data, we are able to reduce the Pearson correlation association between treatment and covariates substantially, with a mean absolute Pearson correlation coefficient of 0.03. A common strategy to further improve balance is to progressively prune observations contributing most to imbalance (Ho et al., 2007; King et al., 2017). When applying this method to the present data by progressively deleting observations with the smallest weights, we found that imbalance increased, contrary to our expectation. We therefore did not seek to further improve balance on our selected treatment.[6]. Once found, balancing weights are integrated into our statistical analysis with weighted least squares (WLS) regression in the first instance, and then into the SUR by multiplying both the dependent variable $\mathbf{Y}$ and the covariate matrix $\mathbf{X} = (1, X_1 \dots X_k)$ by $\mathbf{W}^{1/2}$ (the square root of the diagonalised matrix of observational weights) to allow for estimation of the WLS estimator $(\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}\mathbf{Y}$ within the SUR framework.

3.3 OLS and WLS estimates

We first present conventional OLS estimates of the effect of rainfall on the turnout and vote share of the EU Referendum. Unlike SUR, OLS models estimate turnout and vote-share separately, as if these two are independent. Although this assumption is clearly wrong, we nevertheless start with OLS and WLS because these models are simple to interpret.[7]

Table 2 shows the results from estimations of the turnout, and leave vote share. We adopt two modelling strategies for each dependent variable. Models 1 and 3 estimate ordinary least squares with

[6]This finding is not a universal property of npCBGPS weights, as we found pruning improved balance with other treatment specifications

[7]The OLS and WLS marginal effects are directly interpretable from the estimated coefficients, while the SUR models we later present require logarithmic transformation and visualization.

Table 1: Summary statistics and measures of pre-treatment covariate balance.

	1. Mean	2. SD	3. Correlation with Treatment	4. Correlation with Treatment (npCBGPS)
Outcomes				
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

Note: Column 3 shows Pearson correlations between rainfall and controlling covariates. Column 4 shows Pearson correlations after weighting observations with npCBGPS weights (Fong et al., 2017).

country-level fixed effects, while Models 2 and 4 estimate weighted least squares (WLS) using the npCBGPS observation weights described above. We find that the models perform similarly to each other in the estimation of the effect of rainfall. When predicting turnout, both Models 1 and 2 find a statistically significant effect (in support of **H1**), with Model 2 estimating the larger of the coefficients. Models 3 and 4 find negative rainfall effects on vote share, though only Model 4 is significant, therefore only tentative conclusions can be drawn from OLS estimates on the association between rainfall and vote share.

Turning to the effects of covariates, support for Ukip in the 2014 European Parliament elections significantly increased leave vote share, but also increased turnout, consistent with reports of differential issue saliency between campaigns (Dunford and Kirk, 2016; Griffin, 2016; Twyman, 2016). This finding is accompanied by the similar coefficients of median age and the England dummy variable in Models 2 and 4. These both show that support for Brexit was higher in districts with a greater proportion of older English voters, as is now well established (Goodwin and Heath, 2016; Curtice, 2017). These coefficients are mirrored in 2015 General Election turnout and Higher Education, both of which increase turnout but decrease leave vote share.

Table 2: OLS estimates of UK EU Referendum turnout and vote share.

	Turnout (%)		Leave (%)	
	Model 1	Model 2	Model 3	Model 4
Rain 6am-10pm (mm)	-0.05^{*}	-0.06^{**}	-0.05	-0.09^{*}
	(0.02)	(0.02)	(0.04)	(0.04)
Turnout 2015 GE (%)	0.40^{***}	0.30^{***}	-0.35^{***}	-0.38^{***}
	(0.03)	(0.03)	(0.07)	(0.06)
UKIP 2014 EP (%)	0.14^{***}	0.18^{***}	0.34^{***}	0.37^{***}
	(0.02)	(0.02)	(0.05)	(0.04)
Women (%)	-0.02	0.08	-1.34^{***}	-1.37^{***}
	(0.15)	(0.16)	(0.34)	(0.34)
Low Social Grade (%)	-0.33^{***}	-0.37^{***}	-0.28^{***}	-0.32^{***}
	(0.03)	(0.03)	(0.07)	(0.06)
ln(Pop. Density)	-0.51^{***}	-0.52^{***}	0.14	0.68^{**}
	(0.11)	(0.11)	(0.24)	(0.23)
Higher Education (%)	0.03	0.05	-0.94^{***}	-0.92^{***}
	(0.03)	(0.03)	(0.07)	(0.06)
Median Age	0.18^{***}	0.13^{**}	0.45^{***}	0.60^{***}
	(0.04)	(0.04)	(0.09)	(0.09)
England		1.96^{***}		4.39^{***}
		(0.42)		(0.91)
Constant	44.98^{***}	45.88^{***}	149.99^{***}	141.29^{***}
	(6.99)	(7.38)	(15.64)	(16.14)
Fixed Effects	✓		✓	
npCBGPS Weights		✓		✓
R^2	0.91	0.90	0.87	0.87
Adj. R^2	0.90	0.89	0.87	0.87
Num. obs.	398	398	398	398
RMSE	1.71	0.09	3.82	0.20

Note: Significance stars at $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models 1 and 3 include country level fixed effects (England, Scotland, Wales and Northern Ireland), while Models 2 and 4 include npCBGPS weights to correct for imbalance across the dataset including whether or not a district is located in England. Instead of country-level fixed effects, WLS models include a dummy variable indicating whether the electoral area is England or not. This is done because Scotland, Wales and Northern Ireland contain too few districts to achieve acceptable balance without dropping observations.

3.4 Compositional Analysis with Seemingly Unrelated Regression

Next, we follow Tomz et al. (2002) and Horiuchi and Kang (2017) in estimating two regression equations simultaneously via SUR. The estimation technique solves two problems with the single equation estimation. The first problem, inherent in all uses of OLS to estimate compositional data (data in which outcomes are expressed as proportions adding up to 1), is that OLS could predict a turnout of above 100% or below 0%. The second problem, as indicated previously, is that single equation regressions cannot estimate all three election results (remain, leave and the rate of abstention) at once, leading one to make inferences over a single outcome (leave vote share), ignoring the fact that an effect on one outcome (turnout) automatically affects another. This makes analysis over phenomena such as differential turnout all but impossible. The method applied here corrects both problems through the use of the multinomial logistic transformation and SUR.

Instead of estimating single outcomes, the method estimates logged ratios of election outcomes relative to a baseline outcome. In this case both leave and remain (measured as the percentage relative to the electorate of each district) are expressed as separate outcomes relative the rate of abstention. We therefore create two dependent variables:

$$R_A = \ln\left(\frac{\textit{Remain}\ (\%)}{\textit{Abstain}\ (\%)}\right);\ L_A = \ln\left(\frac{\textit{Leave}\ (\%)}{\textit{Abstain}\ (\%)}\right) \tag{1}$$

We then estimate these dependent variables simultaneously in a system of two regression equations using SUR. When evaluating this model, we recover predicted values by applying the inverse logistic function in terms of percent leave ($\hat{L}$), percent remain ($\hat{R}$) and percent abstain ($\hat{A}$).[8]

$$\hat{L} = \frac{e^{L_A}}{1 + e^{L_A} + e^{R_A}};\ \hat{R} = \frac{e^{R_A}}{1 + e^{L_A} + e^{R_A}};\ \hat{A} = \frac{1}{1 + e^{L_A} + e^{R_A}} \tag{2}$$

Table 3 shows the results of Models 5 and 6 in reduced form.[9]. Model 5 shows a fixed effects model in an analogous configuration to Models 1 and 3, while Model 6 gives estimates of SUR regression with balancing weights. Both models find statistical significance for the effect of rainfall, though Model 6 suggests a greater magnitude of effect.

[8] In all cases $\hat{L}_i + \hat{R}_i + \hat{A}_i = 1$.

[9] Full regression tables provided in the Appendix

Table 3: SUR estimates of logged ratio Referendum results.

	Model 5		Model 6	
	R_A	L_A	R_A	L_A
Rain 6 am-10 pm (mm)	-0.0027^{*}	-0.0046^{**}	-0.0030^{**}	-0.0066^{***}
	(.0012)	(0.0016)	(0.0011)	(0.0015)
Controls	✓	✓	✓	✓
npCBPS Weights			✓	✓
Fixed Effects	✓	✓		
R^2	0.91	0.89	0.91	0.87
Adj. R^2	0.90	0.88	0.90	0.87
RMSE	0.10	0.13	0.01	0.01
Num. obs.	398	398	398	398

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

Note: Significance stars at $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models 5 and 6 show summarised results from simultaneous estimations of leave share and remain share relative to the rate of abstention (see Equation 1).

We display meaningful interpretation of Model 6 in Figure 3. Here we take predicted first differences of a change in rainfall from 0 mm rainfall to 25 mm (approximately 1 inch) between 6 am and 10 pm. We simulate 1,000 coefficient vectors according to a multivariate normal distribution with means set at the coefficient point estimates and sigma set to the variance-covariance matrix of the coefficients. We then multiply the simulated coefficients with rainfall set to 25 mm and then with rainfall set to 0 mm (all other X values are set at their respective means) and subtract one from the other. We display the means of these distributions as point estimates and the 97.5th percentile and the 2.5th percentile as upper and lower bounds.

A first difference of 25 mm rainfall is above the maximum value of rainfall in the time period measured, but we estimate it to compare with estimates of the rainfall effect from the literature (Gomez et al., 2007; Eisinga et al., 2011; Horiuchi and Kang, 2017). We find a relatively high effect on turnout with approximately 1 inch of rainfall equating to a 2.45% rise in the rate of abstention compared with roughly 1% elsewhere. However, these estimates are not directly comparable because of the fact that we are able to restrict out measurements to actual voting hours (a 16 hour window) whereas previous studies had to rely on full 24 hour measurements, including rainfall after the polls had closed. We can make a simple adjustment to our estimate by multiplying our estimate by 2/3 (since 16 hours is two-thirds of a full day), giving a 1.6% effect on turnout. This figure is still high but close to the standard findings in the literature. Figure 3 also shows that rainfall, perhaps surprisingly, affected the leave vote share more than the remain vote share. An increase in rainfall of 25 mm shows a significant decline in the leave vote (-2.89%), while the change to the remain share is smaller (0.44%) and statistically insignificant at the 95% level.

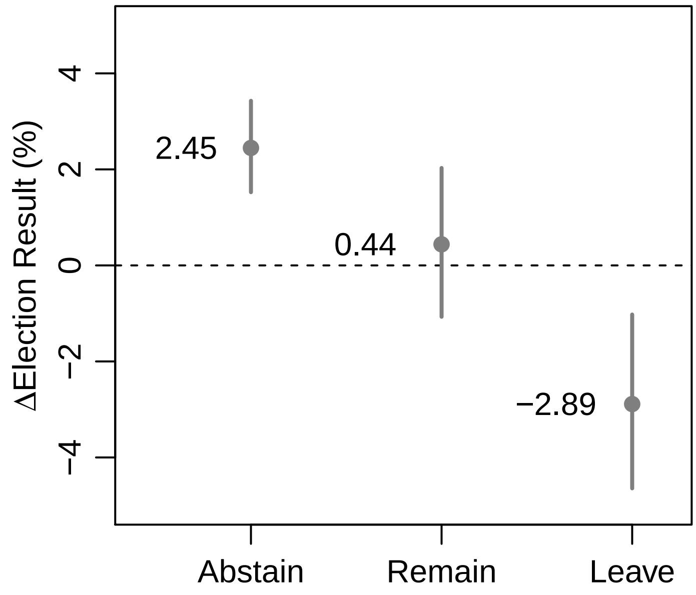

Figure 3: First difference estimates of referendum results from Model 6 at the district level according to a 25 mm increase in rainfall

3.4.1 Differential Turnout or Vote-Shift? Decomposition of the Rainfall Effect

According to recent research connecting psychology with electoral studies (Horiuchi and Kang, 2017; Bassi and Williams, 2017; Meier et al., 2016), poor weather may impact on voting patterns in different ways. Conventional thought has it that rainfall affects elections by deterring supporters of one party more than it does another, but compositional analysis of elections shows that this cannot always be the case. Under certain conditions, at least some proportion of the rainfall effect must come through a vote-shift channel, where according to theory, adverse weather conditions cause undecided voters to become temporarily more risk-averse, thus voting for the least risky candidate.

Regarding the EU referendum, our theoretical expectations were split into two parts. Under differential turnout, predictions for the direction of effect were complicated by conflicting arguments about voter commitment. We show in Figure 3 that the effect of rainfall on remain vote share was insignificant (allowing us to reject **H2a**), while the effect on leave vote share was negative and significant (supporting **H2b**). Under vote-shift, we hypothesised that the remain result would benefit because it represented the *status quo* option (**H3**).

In order to explore how much of the remain advantage was due to either differential turnout (**H2b**) or vote-shift **H3**, we must rely on calculating the upper and lower bounds of the vote-shift channel, since it is not possible to report this precisely from the regression model.[10] First, we find the theoretical upper

[10]See Horiuchi and Kang (2017) for thorough explanation of the method

and lower bounds of the vote-shift channel using the first differences calculated from Model 6:

$$U.B. = \Delta\hat{R}(0.44) - \Delta\hat{L}(-2.89) = 3.33 \tag{3}$$

$$L.B. = U.B(3.33) - \Delta\hat{A}(2.45) = 0.88 \tag{4}$$

Where the upper bound is the entire remain advantage, and the lower bound subtracts $\Delta\hat{A}$ from the upper bound. Under conditions in which the $U.B.$ (remain advantage) $> \Delta\hat{A}$, the vote-shift channel must account for some proportion of vote share advantage, since the decrease in turnout is not enough to explain the entire remain advantage. However, where $U.B.$ (remain advantage) $< \Delta\hat{A}$, differential turnout may explain all of the difference in vote share, meaning that the existence of a vote-shift channel cannot be confirmed. According to Model 6, the lower bound is above zero and we therefore find that the explanation for the remain advantage was mixed. At least 26% of the remain rainfall advantage was due to vote-shift (voters choosing to change vote due to inclement weather).

We also find evidence to suggest that differential turnout (**H2b**) could have been driven by factors identified in our theoretical discussion: social class and age. We run three interactive models (full results in the Appendix) showing that the interactions of rainfall with age and social class had a stronger effect on Brexit support, suggesting that rain had a stronger effect in districts with a greater proportion of older and poorer voters. Turnout in the previous General Election also impacted the rainfall effect on turnout but these effects were evenly spread between leave and remain voter groups. This leads us to conclude that a likely contributor to differential vote share in the EU Referendum was a deterrent effect of rainfall in districts with a high proportion of older and poorer voters.

Since our chosen method of measuring rainfall in Model 6 is more or less conventional, we recognise that there could be better ways to test for the existence of a vote-shift channel. Since vote-shift is said to occur via a psychological mechanism, it may be more effective to measure rainfall in terms of length of exposure, rather than measured amounts. Measurement in millimetres could easily equate a typical rainy day with an otherwise sunny day punctuated by a rainstorm, while the psychological effects of these alternatives could be very different. Motivated by measurements in Bassi and Williams (2017), we test an alternative aggregation of the radar data by calculating the average number of minutes' rainfall experienced by each voting district within voting hours. Taking predicted values, we find $\Delta\hat{A} = 0.64, \Delta\hat{R} = 0.7$ and $\Delta\hat{L} = -1.34$.[11] We calculate a vote-shift upper bound of 2.04, and a lower bound of 1.4. This suggests when measuring for timed exposure to rainfall, the estimate for the minimum proportion of the remain advantage explained by vote-shift raises to 68%. Such alternative measurements

[11] see full results in the Appendix

of rainfall may be of use in further investigations of the vote-shift channel, as well as studies that seek to link non-political events to electoral outcomes through their effect on mood (for example Busby et al., 2016).

In summary, we find evidence in support of both differential turnout (**H2b**) and vote-shift (**H3**) as drivers of the remain rainfall advantage. Although we cannot reject the possibility that vote-shift accounted for the entire remain advantage (due to the constraints of decomposition), it is most likely that the two factors acted in combination. Interactive models show that the likely explanation for differential turnout was not difference in voting habits between the two groups of supporters. Rather, the rainfall had a disproportionate effect on older and poorer voting areas, disadvantaging the Vote Leave campaign.

3.4.2 What if the Referendum Had Happened on a Sunny Day?

One of the immediate questions raised by studies of rainfall and elections is the 'sunny day' counterfactual question: what if it didn't rain? Indeed Gomez et al. (2007) answered this question to speculate that rainfall may have swung the Electoral College vote in 2000's closely contested U.S. Presidential Election. We now use estimates from Model 6 to show how the referendum results might have been affected if no rain fell in any part of the UK on polling day, showing that despite relatively large estimates of the rainfall effect, it had little substantive impact on the referendum outcome.

We subtract the product of beta and the rainfall measurements for each district from the recorded referendum results $Y_i - \beta^{Rain} X_i^{Rain}$. This results in predicted values for the model output where rainfall is equal to 0 in all districts. From this we calculate 1,000 estimates of $\hat{L}_{(rain=0)}$, $\hat{R}_{(rain=0)}$ and $\hat{A}_{(rain=0)}$ and display the resulting vote share distributions as mean point estimates with 95% confidence intervals in Figure 4.

The conclusion evident from Figure 4 is that rainfall could not have swung the result of the EU referendum. Even by a generous estimation for the remain vote (taking the upper bound of the confidence interval) we calculate that the referendum would have produced a win for Vote Leave: 51.9% to 48.1%, a result almost identical to the actual results, a margin of approximately 1.29 million votes. The more likely 'sunny day' scenario (taking the point estimates in Figure 4) would increase the advantage for Vote Leave: 52.2% - 47.8%, a margin of 1.48 million votes.

The counterfactual sunny day question also allows us to make estimations of the number of votes lost to rainfall in each district. Table 4 shows the five districts in which rainfall had greatest impact for both leave and remain. Unsurprisingly, rain caused the most disruption in terms of lost votes in London and the South East where rainfall was highest. This, combined with the relatively large populations of London boroughs resulted in the largest losses of leave votes - with over 4,000 votes lost in Hillingdon.

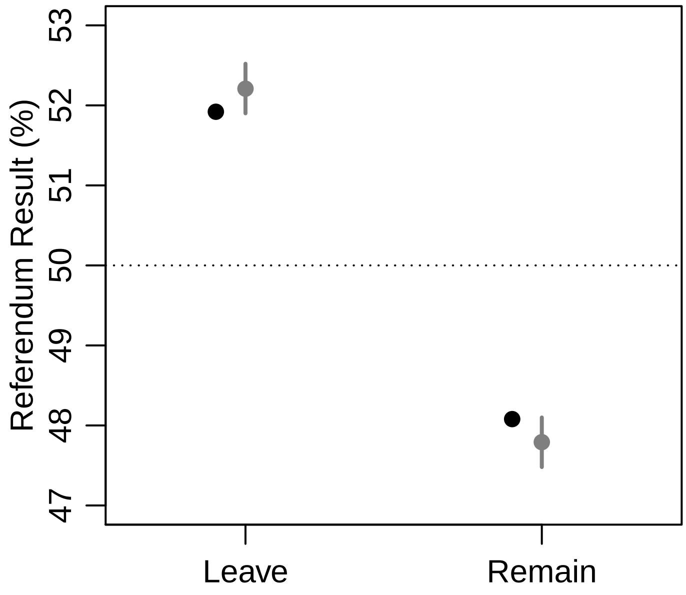

Figure 4: Estimates of the referendum result under conditions with no rainfall (grey dotted segments) compared with the actual referendum result (black dots).

#	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
#	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

Table 4: The top 5 districts most affected by rainfall for both remain and leave

Whilst remain losses were also concentrated in London, the numbers of votes lost due to rainfall were far smaller.

3.4.3 Rainfall and Postal Votes: The Cost of Turning Out

A notable characteristic of the EU referendum was the increased adoption of postal voting. The Electoral Commission (2017) reports that more than 8.5 million people (18.4% of the electorate) requested a postal vote for the referendum, the highest level ever for an election in the UK. Of the 33.6 million votes cast, 26.3 million were cast in person, and the rest were postal or by proxy. 21.79% of all valid votes cast in the referendum were postal. Therefore, the question of whether postal voting could be suppressing the effect of rainfall requires further investigation, as postal votes are not affected by polling day weather. The question is of wider significance to scholars of voting patterns, since postal voting has been shown to eliminate some of the costs associated with voting in person (Karp and Banducci, 2000; Wass et al., 2017; Schelker and Schneiter, 2017). The findings we present below contribute tentatively to this body of evidence.

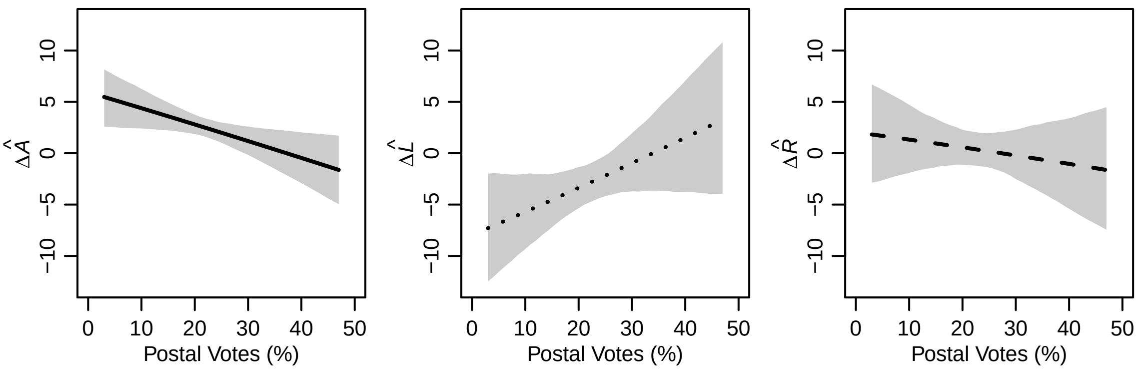

Figure 5: The effect of 25 mm rainfall on referendum results as a function of postal voting. The solid line represents change in the level of abstention ($\Delta\hat{A}$), the dotted line represents change in leave share ($\Delta\hat{L}$) and the dashed line represents change in remain share ($\Delta\hat{R}$).

To test for the impact of postal voting, we include the percentage of postal votes returned in each district into an interactive model with rainfall, otherwise identical to Model 6. We find a significant direct effect of postal voting on R_A, and a significant interactive effect on L_A.[12] Figure 5 illustrates this finding in terms of predicted impact on vote share, revealing that increased postal voting significantly reduces the magnitude of the rainfall effect on both the rate of abstention ($\Delta\hat{A}$) and leave share ($\Delta\hat{L}$). Put simply, districts with high levels of postal voting were less impacted by rainfall than those with low postal vote uptake. These findings support the argument that postal voting eliminates costs associated with voting in person to a degree that is empirically detectable.

3.4.4 Validation: Rainfall in the Error Term of Referendum Forecasting.

Our final piece of analysis is a robustness check, using pre-referendum forecasts of leave share to test whether the addition of rainfall improves vote share prediction. We hypothesise that if our models are correct, rainfall should be contributing to the error in pre-referendum forecasting, causing a slight overestimation of leave share. We take forecasts from a district level polling study using multilevel regression with post-stratification (Lauderdale et al., 2017). Forecasts were made in 379 districts and found a high level of predictive accuracy (.92 Pearson correlation coefficient). We first run a bivariate

[12] See the Appendix for full regression results

OLS regression of final leave share results on forecast results in each district. We then regress the errors of this regression on rainfall, finding a statistically significant negative coefficient equal to a 0.11% reduction in leave share for each 1 mm rainfall. Leave vote share falls by 2.74% per inch of rainfall (25 mm) according to how much error in polling forecasts is due to the unforeseen impact of rainfall. When compared directly with the first difference estimate leave share of Model 6, we come to strikingly similar conclusions. A 25mm increase in rainfall reduces leave share by 3.33% according to Model 6 (once accounting for the rate of abstention). For this reason, we are confident that the rainfall effect is robust to out-of-model applications such as reducing polling error. If election forecasters infer the expected direction and magnitude of rainfall effects from the results of past elections, they may be able to reduce polling error considerably, especially when heavy rain is forecast on election day.

4 Conclusions

In this article, we have incorporated fine grained radar data into the most comprehensive national level analysis of the UK's EU referendum of 2016. We achieved a lower level of voting district disaggregation than the official results, and to our knowledge we present the first electoral analysis of rainfall to restrict the measurement of rainfall to voting hours. Our central conclusion is that rainfall had a substantial effect on voting in several districts, but that the effect was too small to have decisively swung the referendum's final result.

Our key findings for the effect of rainfall on the UK's EU Referendum were as follows. First, we estimate relatively large estimates for the effect of rainfall on turnout. A 25 mm (1 inch) increase in rainfall over 6 am - 10 pm results in a 2.45% decrease in turnout, adjusted to 1.6% for the 24-hour period. Second, contrary to the prediction of Ukip Leader Nigel Farage, we show that leave supporters were in fact more likely to be deterred by rainfall than remain supporters. Third, we show that a counterfactual referendum day without rainfall would most likely have widened the gap between leave and remain, conclusively answering any question of whether rainfall (or lack thereof) could have changed the result.

We also find results of wider interest to election specialists. First, we find that postal voting suppressed the effect of rainfall on turnout and leave share, indicating that postal voting has the effect of nullifying the potential hindrances to voting on polling day. Electoral commissions could therefore do more to reduce the rainfall effect by encouraging alternative voting methods such as free postal voting. Second, we find evidence to support the psychological effects of rainfall on vote share (vote-shift). Third, we find evidence to show that polling analysts may be able to reduce forecasting error by taking into account rain forecasts when the expected direction of effect is known.

What do our findings tell us about the relationship between elections and rainfall in general? Most importantly, our findings suggest that rainfall probably cannot swing the results of referendums or proportionally allocated parliamentary elections unless those elections are extremely close. However, given that we find several districts were likely to have lost thousands of votes in the EU Referendum that was seen as particularly divisive, highly salient and 'close' (at least before the fact), our study shows that there is room for conjecture on the impact of rainfall in close elections elsewhere.

On the one hand, Fraga and Hersh (2011) show that the effect of rainfall in the U.S. Electoral College is confined to elections that are not close, arguing that the weight of get-out-the-vote campaigning in close states helps voters to overcome election day costs. On the other hand, our findings, combined with new psychologically motivated studies of vote-shift (Horiuchi and Kang, 2017) and the impact of apparently irrelevant events on political outcomes (Busby et al., 2016) suggest that the question of the rainfall effect in close elections ought to be revisited – particularly outside the US, where election campaigns are less well funded. Targeted studies of rainfall in close elections may be able to show substantive result altering effects.

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Could Rainfall Have Swung the UK's 2016 EU Referendum? Online Appendix

Contents

A: Aggregation of NIMROD radar data.

The NIMROD System collects radar data for rainfall every five minutes at a resolution of 1 km^2. The data reported for each square on the grid is defined as millimetres of rain per hour multiplied by 32. We have transformed the radar data to ESRI ASCII (.asc) raster format. In order to measure rainfall for the voting period, we limited the time period from 6 AM and 10 PM (official voting hours were between 7 AM and 10 PM). This yields 192 raster images extracted from the NIMROD radar data.[1] As NIMROD measures rainfall in rates of millimetres per hour in five minutes intervals with the additional multiplication of 32 (Met Office, 2003), Equation 1 provides the total amount of rainfall during the period of interest, in terms of millimetres in a 1 km^2 area.

$$Rainfall = \sum_{i=1}^{n=192} \frac{i}{12 \cdot 32} \tag{1}$$

The simple calculation above gives summed rainfall in millimetres for each 1km square of the radar raster image between the period of 6 AM and 10 PM. We then overlay election district polygons and calculate a district mean for squares within the boundaries of the district.[2] This gives a highly precise estimate of average rainfall within each electoral district for the given time period.

[1] We also take an interval between 0000h and 2200h, yielding 264 raster images

[2] Our criterion for inclusion in each district polygon was $>$ 50% of the raster square within the boundary line.

B: Regression when using rainfall 12 midnight to 10pm

This section gives models 1 to 6. We find that the effect of rainfall per mm is smaller due to the larger quantities of rain involved, but that its effect is still statistically significant in Models 1, 2, 5, and 6.

Table 1: Models 1-4 using a measure of rainfall with 12 midnight to 10 pm.

	Model 1	Model 2	Model 3	Model 4
Rain 12 midnight -10 pm (mm)	-0.02^{**}	-0.02^{***}	-0.00	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)
Turnout 2015 GE (%)	0.39^{***}	0.32^{***}	-0.35^{***}	-0.44^{***}
	(0.03)	(0.02)	(0.07)	(0.05)
UKIP 2014 EP (%)	0.14^{***}	0.19^{***}	0.34^{***}	0.42^{***}
	(0.02)	(0.02)	(0.05)	(0.04)
Women (%)	-0.01	-0.05	-1.35^{***}	-1.34^{***}
	(0.15)	(0.17)	(0.34)	(0.36)
Low Social Grade (%)	-0.33^{***}	-0.32^{***}	-0.27^{***}	-0.23^{***}
	(0.03)	(0.03)	(0.07)	(0.06)
ln(Pop. Density)	-0.45^{***}	-0.40^{***}	0.15	0.41
	(0.11)	(0.10)	(0.24)	(0.22)
Higher Education (%)	0.03	0.11^{***}	-0.94^{***}	-0.80^{***}
	(0.03)	(0.03)	(0.07)	(0.06)
Median Age	0.18^{***}	0.16^{***}	0.47^{***}	0.51^{***}
	(0.04)	(0.04)	(0.09)	(0.09)
England		1.90^{***}		3.67^{***}
		(0.39)		(0.84)
countryNorthern Ireland	-1.47		-4.57^{**}	
	(0.76)		(1.71)	
countryScotland	-5.01^{***}		-7.58^{***}	
	(0.56)		(1.26)	
countryWales	-0.48		-2.62^{**}	
	(0.40)		(0.91)	
Constant	44.92^{***}	47.06^{***}	149.61^{***}	141.64^{***}
	(6.95)	(7.77)	(15.66)	(16.64)
R^2	0.91	0.91	0.87	0.88
Adj. R^2	0.91	0.91	0.87	0.88
Num. obs.	398	398	398	398
RMSE	1.70	0.09	3.83	0.18

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

Table 2: Models 5 and 6 using a measure of rainfall with 12 midnight to 10 pm.

	Model 5 (midnight-10 pm)	Model 6 (midnight-10 pm)
eq1: X(Intercept)	0.9391 (0.5518)	0.9896 (0.6305)
eq1: Xrf_0022	-0.0017 (0.0006)**	-0.0016 (0.0005)**
eq1: XTurnout15	0.0137 (0.0024)***	0.0053 (0.0019)**
eq1: XUKIP14_pct	0.0118 (0.0017)***	0.0164 (0.0014)***
eq1: XfemPerc	-0.0228 (0.0120)	-0.0248 (0.0137)
eq1: XpercDE	-0.0271 (0.0023)***	-0.0256 (0.0023)***
eq1: XlogPop	-0.0261 (0.0086)**	-0.0223 (0.0084)**
eq1: XpercDegree	-0.0223 (0.0023)***	-0.0138 (0.0022)***
eq1: XmedianAge	0.0179 (0.0033)***	0.0177 (0.0034)***
eq1: XcountryNorthern Ireland	-0.2071 (0.0603)***	
eq1: XcountryScotland	-0.4798 (0.0442)***	
eq1: XcountryWales	-0.0776 (0.0320)*	
eq2: X(Intercept)	-3.2285 (0.4172)***	-2.7684 (0.4499)***
eq2: Xrf_0022	-0.0015 (0.0004)***	-0.0014 (0.0004)***
eq2: XTurnout15	0.0279 (0.0018)***	0.0234 (0.0014)***
eq2: XUKIP14_pct	-0.0022 (0.0013)	-0.0010 (0.0010)
eq2: XfemPerc	0.0330 (0.0091)***	0.0292 (0.0098)**
eq2: XpercDE	-0.0152 (0.0018)***	-0.0157 (0.0017)***
eq2: XlogPop	-0.0309 (0.0065)***	-0.0365 (0.0060)***
eq2: XpercDegree	0.0181 (0.0017)***	0.0202 (0.0016)***
eq2: XmedianAge	-0.0009 (0.0025)	-0.0026 (0.0025)
eq2: XcountryNorthern Ireland	-0.0116 (0.0456)	
eq2: XcountryScotland	-0.1680 (0.0335)***	
eq2: XcountryWales	0.0320 (0.0242)	
eq1: XEngland		0.2000 (0.0317)***
eq2: XEngland		0.0458 (0.0226)*
eq1: R^2	0.8875	0.8807
eq2: R^2	0.9089	0.9276
eq1: Adj. R^2	0.8843	0.8779
eq2: Adj. R^2	0.9063	0.9259
Num. obs. (total)	398	398

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

C: Full results tables of models 5 & 6 from the paper

	Model 5	Model 6
eq1: X(Intercept)	0.9553 (0.5520)	0.8034 (0.5989)
eq1: Xrf_0622	-0.0046 (0.0016)**	-0.0066 (0.0015)***
eq1: XTurnout15	0.0138 (0.0024)***	0.0071 (0.0022)**
eq1: XUKIP14_pct	0.0119 (0.0017)***	0.0155 (0.0014)***
eq1: XfemPerc	-0.0228 (0.0120)	-0.0175 (0.0126)
eq1: XpercDE	-0.0269 (0.0023)***	-0.0296 (0.0024)***
eq1: XlogPop	-0.0304 (0.0085)***	-0.0209 (0.0087)*
eq1: XpercDegree	-0.0227 (0.0023)***	-0.0199 (0.0023)***
eq1: XmedianAge	0.0175 (0.0033)***	0.0171 (0.0033)***
eq1: XcountryNorthern Ireland	-0.1880 (0.0610)**	
eq1: XcountryScotland	-0.4815 (0.0442)***	
eq1: XcountryWales	-0.0814 (0.0320)*	
eq2: X(Intercept)	-3.2276 (0.4208)***	-2.9527 (0.4451)***
eq2: Xrf_0622	-0.0027 (0.0012)*	-0.0030 (0.0011)**
eq2: XTurnout15	0.0282 (0.0018)***	0.0222 (0.0017)***
eq2: XUKIP14_pct	-0.0023 (0.0013)	0.0000 (0.0011)
eq2: XfemPerc	0.0323 (0.0091)***	0.0387 (0.0094)***
eq2: XpercDE	-0.0145 (0.0018)***	-0.0161 (0.0018)***
eq2: XlogPop	-0.0347 (0.0065)***	-0.0472 (0.0065)***
eq2: XpercDegree	0.0178 (0.0018)***	0.0191 (0.0017)***
eq2: XmedianAge	-0.0006 (0.0025)	-0.0073 (0.0025)**
eq2: XcountryNorthern Ireland	-0.0035 (0.0465)	
eq2: XcountryScotland	-0.1713 (0.0337)***	
eq2: XcountryWales	0.0307 (0.0244)	
eq1: XEngland		0.2116 (0.0337)***
eq2: XEngland		0.0294 (0.0251)
eq1: R^2	0.8874	0.8744
eq2: R^2	0.9073	0.9055
eq1: Adj. R^2	0.8842	0.8714
eq2: Adj. R^2	0.9047	0.9033
Num. obs. (total)	398	398

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

Table 3: Full results of Models 5 and 6. Note that eq1 refers to L_A and eq2 refers to R_A.

D: Full results of other models used in the paper

Here we give full results of rain minutes model used in section: **Differential Turnout or Vote-Shift? Decomposition of the Rainfall Effect** and the interaction model used in the section: **Rainfall and Postal Votes: The Cost of Turning Out**

	Interactive Model	Model using rainfall minutes
eq1: X(Intercept)	0.7575 (0.5969)	1.2115 (0.6408)
eq1: Xrf_0622	-0.0174 (0.0051)***	
eq1: Xminutes_0622		-0.0001 (0.0000)
eq1: XTurnout15	0.0063 (0.0024)**	0.0072 (0.0021)***
eq1: XUKIP14_pct	0.0155 (0.0014)***	0.0176 (0.0014)***
eq1: XfemPerc	-0.0138 (0.0128)	-0.0310 (0.0136)*
eq1: XpercDE	-0.0296 (0.0024)***	-0.0231 (0.0023)***
eq1: XlogPop	-0.0255 (0.0092)**	-0.0344 (0.0090)***
eq1: XpercDegree	-0.0198 (0.0023)***	-0.0165 (0.0022)***
eq1: XmedianAge	0.0162 (0.0034)***	0.0173 (0.0036)***
eq1: XEngland	0.2111 (0.0336)***	0.1882 (0.0310)***
eq1: Xpostal_pct	-0.0024 (0.0017)	
eq1: Xrf_0622:postal_pct	0.0005 (0.0002)*	
eq2: X(Intercept)	-2.9474 (0.4438)***	-2.8005 (0.4697)***
eq2: Xrf_0622	-0.0060 (0.0038)	
eq2: Xminutes_0622		-0.0000 (0.0000)
eq2: XTurnout15	0.0233 (0.0018)***	0.0242 (0.0016)***
eq2: XUKIP14_pct	0.0003 (0.0011)	0.0004 (0.0010)
eq2: XfemPerc	0.0370 (0.0095)***	0.0247 (0.0100)*
eq2: XpercDE	-0.0155 (0.0018)***	-0.0132 (0.0017)***
eq2: XlogPop	-0.0443 (0.0069)***	-0.0370 (0.0066)***
eq2: XpercDegree	0.0195 (0.0017)***	0.0207 (0.0016)***
eq2: XmedianAge	-0.0066 (0.0025)**	-0.0005 (0.0026)
eq2: XEngland	0.0280 (0.0250)	0.0195 (0.0227)
eq2: Xpostal_pct	-0.0026 (0.0013)*	
eq2: Xrf_0622:postal_pct	0.0001 (0.0002)	
eq1: R^2	0.8760	0.8650
eq2: R^2	0.9066	0.8981
eq1: Adj. R^2	0.8725	0.8619
eq2: Adj. R^2	0.9040	0.8957
Num. obs. (total)	398	398

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

Table 4: Regression tables for interactive models and rainfall time using minutes. Note that eq1 refers to L_A and eq2 refers to R_A.

E: Predicted values plot calculated from rainfall minutes model

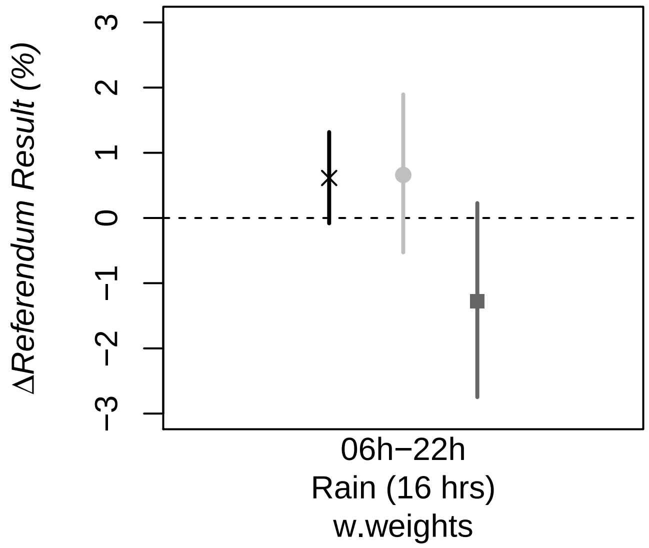

Figure 1: Predicted values for the model quoted in section: **Differential Turnout or Vote-Shift? Decomposition of the Rainfall Effect**. The crossed black line shows the effect of 960 minutes of rainfall (16 hours) on the rate of abstention. The dotted grey line shows the effect on remain share, and the squared dark grey line shows the effect on leave share. The imbalance in this model was extremely low (the mean absolute Pearson correlation between treatment and covariates was 0.0002). The calculations of upper bound and lower bound for the vote shift effect when measuring minutes of rainfall correspond directly to this graph.

F: Interactive models to determine source of differential turnout

Here we show models described in section: **Differential Turnout or Vote-Shift? Decomposition of the Rainfall Effect**. Interactive models show the impact of social class, age, and previous district level turnout on the rainfall effect. We find that there is mixed evidence for all three factors affecting the rainfall effect on turnout. However, only social class and age show differential effects on remain and leave (and only social class is significant). This suggests that contributors to the differential turnout effect found in the paper could have been due to a stronger effect on poorer and older populations. While previous election turnout impacted the rainfall effect, it did so similarly for both leave and remain, meaning that previous election turnout was an unlikely source of differential vote share.

	Social Class	Age	Previous Election Turnout
eq1: X(Intercept)	0.6830 (0.5969)	0.6675 (0.6096)	1.3008 (0.6294)*
eq1: Xrf_0622	0.0084 (0.0062)	0.0096 (0.0139)	−0.0667 (0.0248)**
eq1: XTurnout15	0.0077 (0.0022)***	0.0073 (0.0022)**	0.0037 (0.0026)
eq1: XUKIP14_pct	0.0154 (0.0014)***	0.0157 (0.0014)***	0.0153 (0.0014)***
eq1: XfemPerc	−0.0158 (0.0126)	−0.0166 (0.0127)	−0.0225 (0.0127)
eq1: XpercDE	−0.0275 (0.0025)***	−0.0294 (0.0024)***	−0.0300 (0.0024)***
eq1: XlogPop	−0.0250 (0.0088)**	−0.0207 (0.0087)*	−0.0219 (0.0086)*
eq1: XpercDegree	−0.0208 (0.0023)***	−0.0200 (0.0023)***	−0.0199 (0.0023)***
eq1: XmedianAge	0.0162 (0.0033)***	0.0188 (0.0037)***	0.0171 (0.0033)***
eq1: XEngland	0.2185 (0.0336)***	0.2116 (0.0337)***	0.2063 (0.0336)***
eq2: X(Intercept)	−2.9789 (0.4468)***	−2.9345 (0.4538)***	−2.5570 (0.4672)***
eq2: Xrf_0622	0.0003 (0.0047)	−0.0051 (0.0103)	−0.0508 (0.0184)**
eq2: XTurnout15	0.0223 (0.0017)***	0.0221 (0.0017)***	0.0195 (0.0019)***
eq2: XUKIP14_pct	−0.0000 (0.0011)	−0.0000 (0.0011)	−0.0002 (0.0011)
eq2: XfemPerc	0.0391 (0.0094)***	0.0386 (0.0094)***	0.0348 (0.0095)***
eq2: XpercDE	−0.0157 (0.0019)***	−0.0162 (0.0018)***	−0.0164 (0.0018)***
eq2: XlogPop	−0.0481 (0.0066)***	−0.0473 (0.0065)***	−0.0481 (0.0064)***
eq2: XpercDegree	0.0189 (0.0017)***	0.0191 (0.0017)***	0.0191 (0.0017)***
eq2: XmedianAge	−0.0074 (0.0025)**	−0.0075 (0.0027)**	−0.0072 (0.0025)**
eq2: XEngland	0.0309 (0.0252)	0.0294 (0.0251)	0.0251 (0.0249)
eq1: Xrf_0622:percDE	−0.0006 (0.0002)*		
eq2: Xrf_0622:percDE	−0.0001 (0.0002)		
eq1: Xrf_0622:medianAge		−0.0004 (0.0003)	
eq2: Xrf_0622:medianAge		0.0001 (0.0003)	
eq1: Xrf_0622:Turnout15			0.0009 (0.0004)*
eq2: Xrf_0622:Turnout15			0.0007 (0.0003)**
eq1: R^2	0.8763	0.8748	0.8762
eq2: R^2	0.9056	0.9055	0.9071
eq1: Adj. R^2	0.8731	0.8716	0.8730
eq2: Adj. R^2	0.9032	0.9030	0.9047
Num. obs. (total)	398	398	398

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

Table 5: Regression table for models with interaction effects mentioned in discussion on differential turnout. Note that eq1 refers to L_A and eq2 refers to R_A. The interactions of rain with social class (left) and age (centre) produce differing effects for both L_A and R_A. The interaction between previous election turnout (2015 General Election) and rainfall produces significant results for both equations, with similar effects for both L_A and R_A.

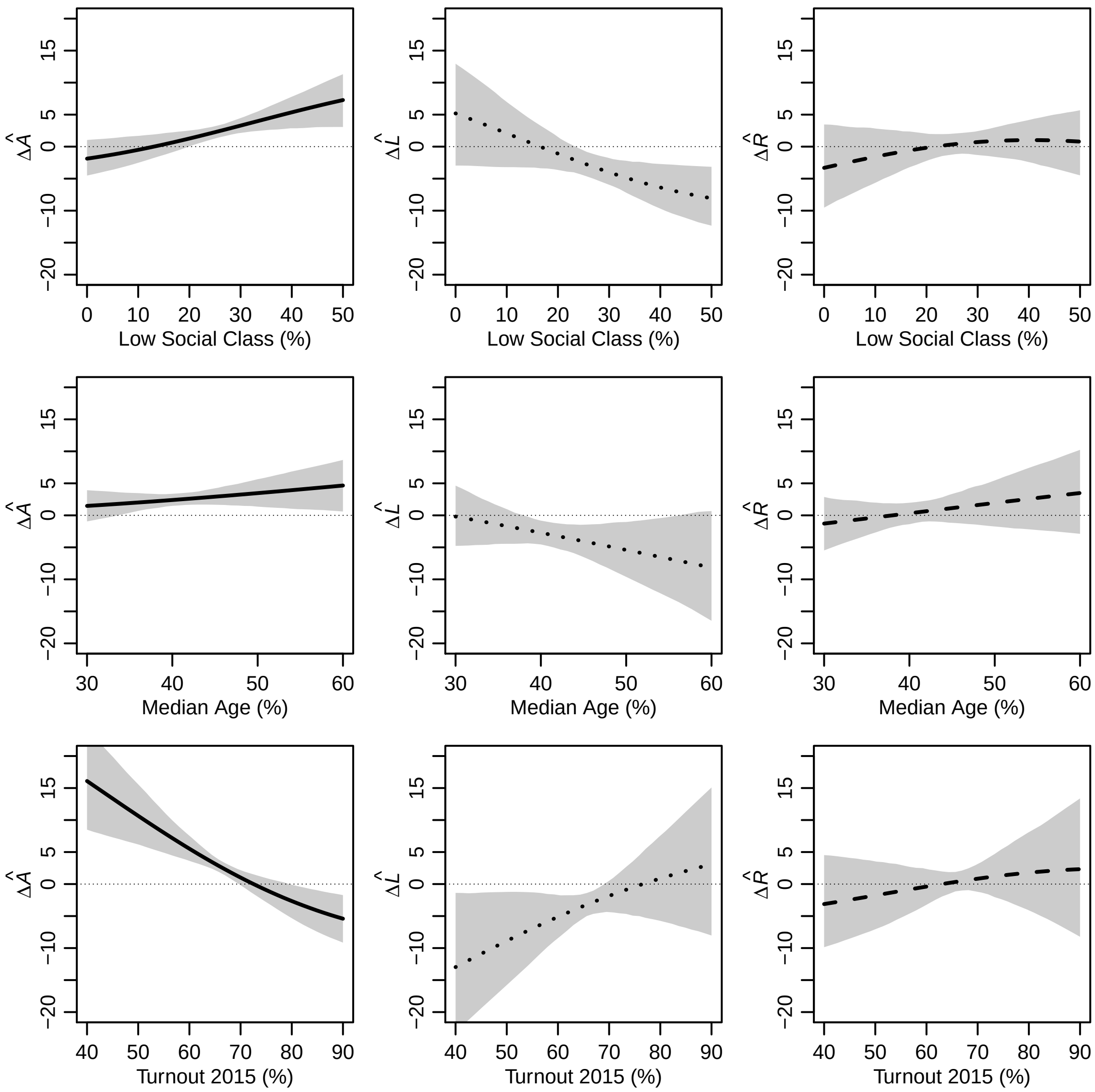

Figure 2: Interaction plot showing the impact of social class, age, and previous election turnout on the rainfall effect. While all three variables impact the rain effect on turnout, only age and social class affect leave and remain vote shares differently.

References

Met Office (2003). *1 Km Resolution UK Composite Rainfall Data from the Met Office Nimrod System. NCAS British Atmospheric Data Centre.* URL: `http://catalogue.ceda.ac.uk/uuid/27dd6ffba67f667a18c62de5c3456350` (visited on 12/15/2016).