Did terrorism affect voting in the Brexit referendum?

APPENDIX

For online publication

A. Region-Level analysis: Spillover Effects

A.1 Motivation and description of control variables

Several recent studies have identified potential determinants of the Brexit vote at both the individual and the region level; see Becker et al. (2017), but also Langella and Manning (2016); Goodwin and Milazzo (2017); Clarke et al. (2017); Liberini et al. (2017); Chan et al. (2017); Colantone and Stanig (2018); Pickard (2019). We capture these determinants through our broad set of control variables.

Our first set of variables reflects elements of the two primary narratives set out by Chan et al. (2017): the revolt of the economically 'left-behinds' and the resurgence of English nationalism. As in prior studies, we primarily use district-level data from the 2001 and 2011 censuses, and employ changes and growth rates between these two census years to capture changing trends over time. One of the most robust determinants is educational attainment. More educated individuals can better realize the opportunities that result from EU membership, and thus districts that experience a larger growth of highly educated individuals are more likely to support remain (Becker et al., 2017). Another important predictor is immigration, a central topic throughout the referendum campaign (Goodwin and Heath, 2016; Becker et al., 2017; Colantone and Stanig, 2018). The Leave side argued that immigration needed to be controlled and reduced, whilst making links to migrants using up public services that would otherwise go to UK citizens; for example, the National Health Service. The Remain side, however, argued that migrants are net contributors to the UK economy and provide cultural enrichment and diversity. To capture these arguments, we include growth rates in the local population shares by three origin groups: the 15 'old' EU member states, the 12 states that joined the EU in 2004 and 2007, and non-EU countries. It has also been suggested that the Leave campaign resonated well in the old industrial heartlands of the UK where the manufacturing sector is concentrated, which appealed to the notion of returning jobs that have been outsourced or made redundant by technological progress. Car manufacturers, on the other hand, warned that not having good access to the EU single market after Brexit would make their plants uncompetitive, leading to lost work and possible closure.[1] We account for these claims through the change in the share of the population that are employed in the manufacturing sector. To further capture the general economic conditions, we include the change in median wages between 2005 and 2015 (Bell and Machin, 2016; Becker et al., 2017). Another key topic on the campaign trail was related to the impact of globalization and EU integration. To proxy for this, we include the share of value added in a UK county that can be attributed to consumption and investment demand in the rest of the EU (Los et al., 2017). Finally, to capture changing trends in religious diversity, we control for the change in the share of Muslim population.

Our second set of control variables includes three variables that are correlated with terrorism but may also be relevant for explaining the referendum returns. First, we include a measure of past exposure to terrorist attacks (attack history); namely, a binary indicator coding districts that experienced terrorist attacks between January 1996 and December 2012. Second, we include the total number of crimes and offenses by Police Force Area in England and Wales, and district in Scotland, as a measure of the district's crime level. This captures the fact that terrorists may use criminal gangs to facilitate their attack or target areas which are highly exposed to crime, and, at the same time, these characteristics may affect voting behavior. Third, we include the district's population density, since attacks occur more frequently in densely populated areas (Brodeur, 2018), which were also typically in favor of Remain. Full description of these variables, and the corresponding data sources, are provided in Table A1 below.

Our control variables are all pre-treatment and distinct from one another, which allows us to limit collinearity concerns. However, given the long list of other potential determinants, we perform checks with supplementary controls (see Section 4.2 and Table A2). For comparability, we standardize our continuous right-hand-side variables to have a mean of 0 and a standard deviation of 1.

[1] https://tinyurl.com/j4hewh8

A.2 Figures and Maps

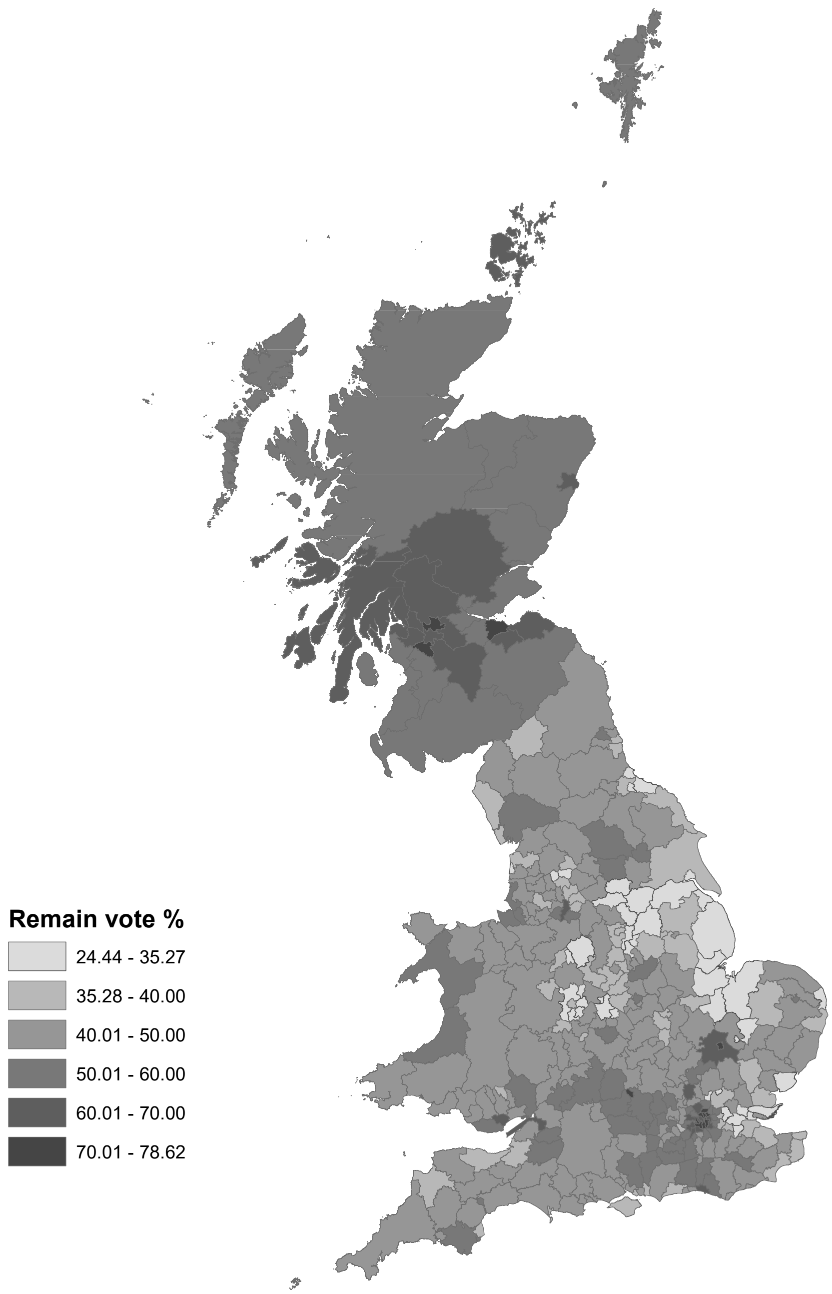

Figure A1: Remain vote share across districts (LADs)

Table A1: Variable definitions and data sources for region-level analysis

Name	Definition	Source
District level		
Dependent variables		
Remain	Remain vote share in the 2016 EU referendum	Electoral Commission
Turnout	Turnout rate in the 2016 EU referendum	Electoral Commission
Main explanatory variable		
Distance	Centroid-to-centroid distance to closest terrorism-hit district in kilometers (January 2013 to referendum date)	Own calculation from GTD
Control variables		
Attack history	=1 if a district has a history of being attacked (Jan 1996 to Dec 2012), 0 otherwise	Own calculation from GTD
Qual. level 4+ share growth	Growth in the share of highly educated population, defined as citizens with level 4+ qualifications (undergraduate degree, professional qualification or equivalent) (2001-2011)	Census - Becker et al. (2017)
Manufacturing employment share change	Change in the share of the population that are employed in the manufacturing sector (2001-2011)	Census - Becker et al. (2017)
EU accession migrant growth	Change in the number of migrants from the 12 EU accession states (2001-2011) relative to the local resident population in 2011	Census - Becker et al. (2017)
EU 15 migrant growth	Change in the number of migrants from the 'old' EU member states (2001-2011) relative to the local resident population in 2011	Census - Becker et al. (2017)
Migrants from elsewhere growth	Change in the number of migrants from non-EU countries (2001-2011) relative to the local resident population in 2011	Census - Becker et al. (2017)
Median hourly pay change	Median hourly pay change (2005-2015)	Census - Becker et al. (2017)
Muslim population change	Growth in the share of Muslim population (2001-2011)	Census
Population density	Total population in 2011 / Area (hectares)	Census
Total crimes and offences	Logarithm of total crimes and offences by Police Force Areas (2012/13-2013/14)	ONS
Total economy EU dependence	Share of value added in a UK region that can be attributed to consumption and investment demand in the rest of the EU (2010)	Los et al. (2017) - Becker et al. (2017)
UKIP support	Share of UKIP supporters calculated by matching BES responses to the local authority districts, and excluding districts with less than 10 respondents	BES wave 8
Austerity shock	Total fiscal cuts, defined as financial loss per working age adult £ per year (2010-2015)	Innes and Tetlow (2015) - Becker et al. (2017)
Pensioner share growth	Growth in the share of population aged 60 or over (2001-2011)	Census - Becker et al. (2017)
Population	Total population / 1000	Census - Becker et al. (2017)
Twitter usage	=1 if district is above the 75th percentile of Twitter usage per capita, 0 otherwise	Own calculation from Follow the Hashtag (2016)
High media coverage	=1 for attacks that received 10 or more LexisNexis hits, 0 otherwise	LexisNexis
Muslim/Jihadi perpetrators	=1 for attacks with Muslim or Jihadi-inspired perpetrators, 0 otherwise	GTD
Fatal outcomes	=1 for attacks with fatal outcomes, 0 otherwise	GTD
UKIP support (2014 EP election)	UKIP vote share in the 2014 European Parliament elections	Electoral Commission
1975 Leave share	Leave vote share in the 1975 EU referendum by county	Becker et al. (2017)
Unemployment rate	Unemployment rate (2015)	LFS - Becker et al. (2017)
No qual. share growth	Growth in the share of population with no qualifications (2001-2011)	Census - Becker et al. (2017)
EU structural funds	EU structural funds per capita (2013)	Becker et al. (2017)
Rural	=1 if a district is defined as "Countryside living" or "Town & country living", 0 otherwise	Census
Ward level		
All variables		
Remain	Remain vote share in the 2016 EU referendum	Rosenbaum (2017)
IMD: average rank	Average rank of the Lower Layer Super Output Area (LSOA) index of multiple deprivation (IMD) within a ward; inverse scaling, higher values means more deprived (2015)	ONS
Population density	Total population (2016) / Area (hectares)	Own calculation
Population	Total population (2016)	ONS
Other variables		
Withdrawal deal support (2018)	Percentage of support for the withdrawal deal	Survation
Invalid votes (2016)	Percentage of invalid votes in the 2016 EU referendum	Electoral Commission
Economy worse?	Share of individuals who believe the economy will be worse after Brexit	BES wave 8
Personal finances worse?	Share of individuals who believe their personal finances will be worse after Brexit	BES wave 8

Notes: ONS refers to the Office for National Statistics. GTD refers to the Global Terrorism Database. LFS refers to the Labour Force Survey.

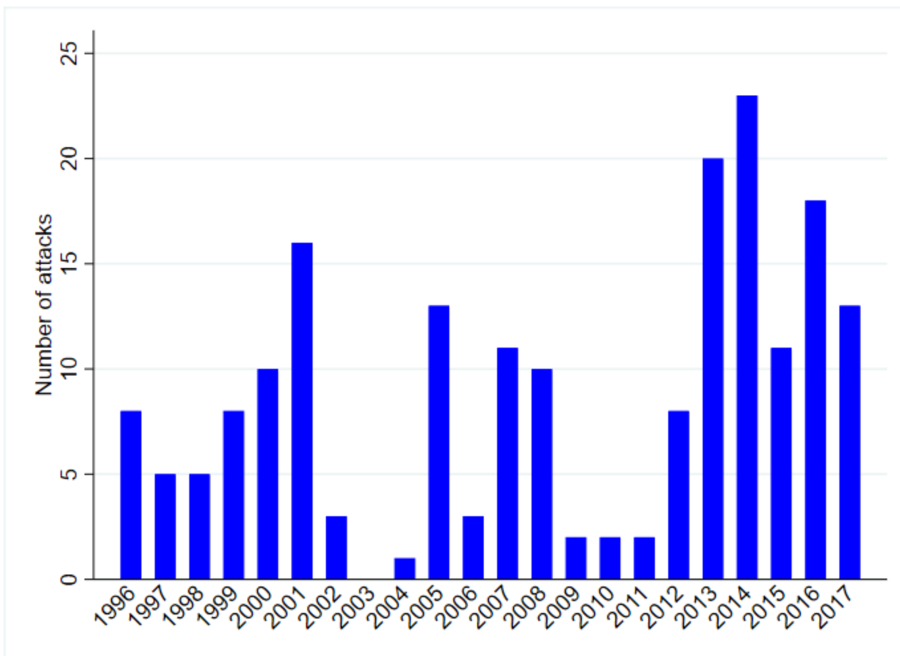

Figure A2: Frequency of terrorist attacks in England, Scotland and Wales from 1996 to 2017

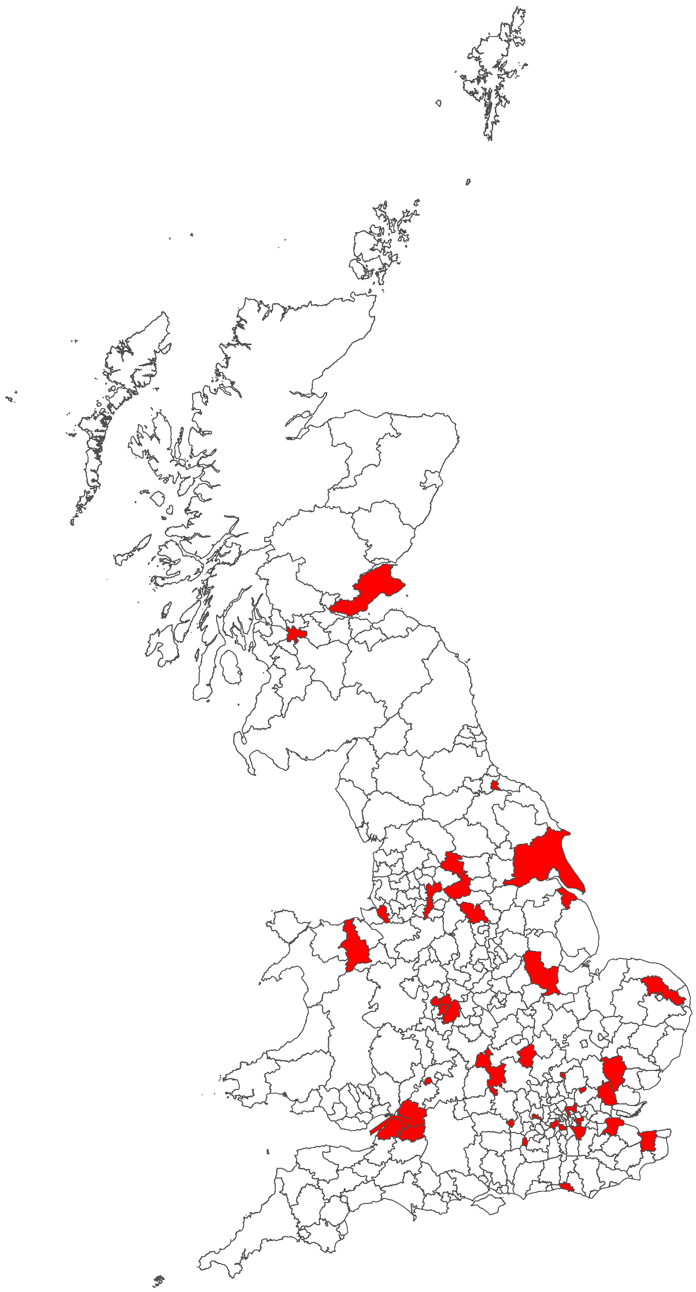

Figure A3: Terrorist-hit districts (LADs)

Notes: Red shades correspond to districts that were hit by terrorist attacks from January 2013 to the referendum date.

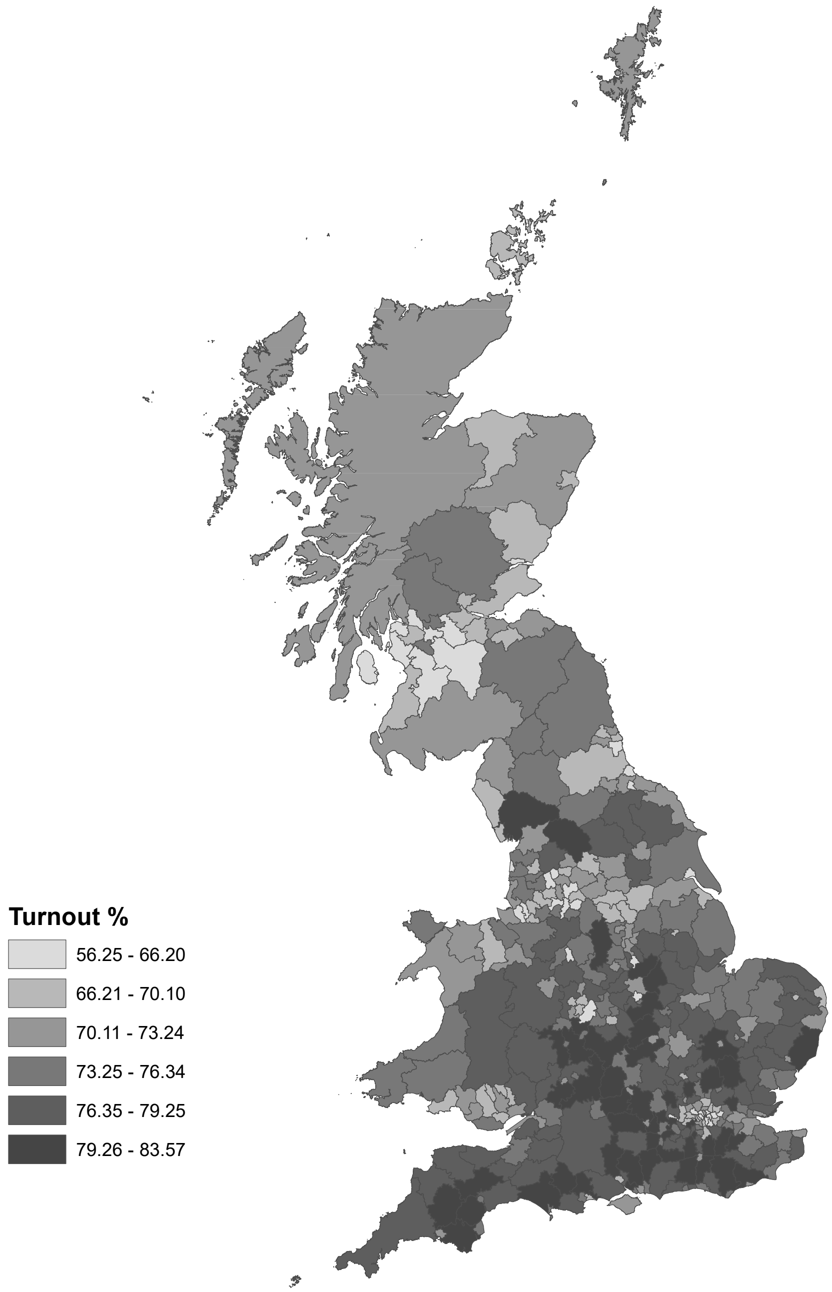

Figure A4: Turnout rate across districts (LADs)

A.3 Extra control variables

In Table A2, we check the sensitivity of our results to including additional regressors. Column (1) reports estimates of the baseline specification, where we control for the variables discussed in Section A.1 (vector $\mathbf{X}_i$). The sign and significance of the estimated coefficients are generally consistent with what has been established in the existing Brexit literature (Becker et al., 2017; Colantone and Stanig, 2018). Column (2) adds the UKIP vote share in the 2014 European Parliament elections, obtained from the Electoral Commission. We do not include this variable throughout our analysis due to high correlation with the Remain vote share (Becker et al., 2017). This is reflected in the value of the R-squared in columns (1) and (2) which jumps from 0.751 to 0.922. Moreover, the European Parliament elections took place during the attack sample period, and thus this variable is, to some extent, post-treatment. Furthermore, it does not portray an accurate representation of the UKIP support, since the turnout rate at the European Parliament elections was only 35.6% and UKIP was the largest party with 26.6% of the national vote. The next six columns include the following variables: the Leave vote share of the 1975 EU referendum (column (3)), the district-level unemployment rate (column (4)), the growth in the population share of citizens with no qualifications (column (5)), the amount of EU structural funds received by each county (column (6)), a binary indicator coding rural districts (column (7)), and the district's turnout rate at the 2016 EU referendum (column (8)). Finally, in column (9), we include all aforementioned variables together. Throughout this exercise, 'Distance' remains negative and statistically significant at conventional levels.

Table A2: Terrorism and the Remain vote: extra control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance	-0.022**	-0.021**	-0.021*	-0.023*	-0.019*	-0.038***	-0.019**	-0.020**	-0.026**
	(0.045)	(0.030)	(0.056)	(0.063)	(0.069)	(0.004)	(0.044)	(0.030)	(0.012)
UKIP support (2014 EP election)		-9.954***							-9.054***
		(0.000)							(0.000)
1975 Leave share			-0.099						-0.333
			(0.868)						(0.525)
Unemployment rate				-1.144**					-0.454**
				(0.035)					(0.034)
Growth of no quals. share					3.976***				1.417***
					(0.000)				(0.001)
EU structural funds						0.782			0.539
						(0.220)			(0.215)
Rural							-1.103		-0.479
							(0.207)		(0.441)
Turnout								0.469***	0.234
								(0.002)	(0.110)
Qual. level 4+ share growth	3.139***	1.461***	3.131***	2.786***	4.355***	3.211***	3.176***	2.334***	1.529***
	(0.001)	(0.006)	(0.001)	(0.002)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
Manufacturing employment share growth	1.495**	1.250***	1.481**	1.219**	0.302	1.828***	1.640***	0.937**	0.584**
	(0.011)	(0.000)	(0.011)	(0.032)	(0.587)	(0.001)	(0.000)	(0.042)	(0.018)
EU accession migrant growth	-1.949**	-0.921***	-1.956**	-1.964**	-2.132***	-0.921	-2.059***	-1.760***	-0.915***
	(0.029)	(0.000)	(0.027)	(0.021)	(0.005)	(0.244)	(0.000)	(0.000)	(0.001)
EU 15 migrant growth	2.913	1.754***	2.911	2.558	2.382	3.158	3.037***	2.599***	1.314**
	(0.142)	(0.002)	(0.142)	(0.202)	(0.166)	(0.105)	(0.000)	(0.000)	(0.012)
Migrants from elsewhere growth	1.145	-1.580**	1.150	1.337	0.766	0.455	1.057*	1.829***	-1.226*
	(0.397)	(0.019)	(0.394)	(0.327)	(0.541)	(0.727)	(0.090)	(0.005)	(0.077)
Median hourly pay change	-0.708**	-0.209	-0.705**	-0.533	-0.404	-0.553	-0.699**	-0.541	0.178
	(0.032)	(0.425)	(0.033)	(0.156)	(0.241)	(0.118)	(0.045)	(0.119)	(0.519)
Muslim population growth	0.450	-0.390	0.454	0.421	0.398	0.372	0.484	0.528	-0.331
	(0.448)	(0.126)	(0.444)	(0.470)	(0.470)	(0.527)	(0.231)	(0.185)	(0.179)
Population density	2.273**	0.170	2.277**	2.565**	2.960***	2.105*	2.056***	3.298***	1.261**
	(0.036)	(0.742)	(0.035)	(0.034)	(0.007)	(0.064)	(0.007)	(0.000)	(0.034)
Total crimes and offences	-0.244	-0.351	-0.218	-0.109	-0.389	-0.239	-0.122	-0.373	-0.128
	(0.768)	(0.529)	(0.802)	(0.911)	(0.602)	(0.746)	(0.855)	(0.568)	(0.816)
Total economy EU dependence	-0.846	-0.179	-0.877	-0.996	-1.297	-0.760	-0.718	-1.178*	-0.296
	(0.368)	(0.645)	(0.361)	(0.251)	(0.144)	(0.430)	(0.244)	(0.053)	(0.496)
Attack cluster FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.751	0.922	0.751	0.754	0.789	0.757	0.753	0.760	0.930
Observations	337	337	337	334	337	327	337	337	325

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.4 Sensitivity to time period

In Table A3, we test the robustness of our results to re-constructing the attack distance measure based on a shorter time window or assigning a larger weight to attacks that occurred closer to the referendum date. We start by excluding the attacks that occurred in 2013. Column (1) shows the estimates based on the baseline working sample of non-attacked districts; column (2) includes Government Office Regions (GOR) fixed effects to soak up any residual heterogeneities that are not captured by our attack cluster fixed effects (since the attack clusters now include a larger number of districts); and column (3) introduces the extra controls from our main analysis. We then proceed by running the same regression set-up after excluding the attacks that occurred in 2013 and 2014; that is, we only use the attacks that occurred from January 2015 to the referendum date to calculate our distance measure (columns (4)-(6)). Finally, we re-estimate our baseline specification using weighted regressions, where the weight assigned to each attack cluster is proportional to the time since the most recent attack in that cluster (with more recent attacks receiving a larger weight). We do this first by year and then by quarter (columns (7)-(8)). Our findings persist regardless of the period used or the weight assigned to each attack cluster, and, perhaps more importantly, the magnitudes of the coefficients are similar across specifications.[2]

Table A3: Terrorism and the Remain vote: sensitivity to time period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance	-0.026**	-0.027**	-0.023***	-0.014	-0.018*	-0.016**	-0.023*	-0.022**
	(0.015)	(0.015)	(0.007)	(0.152)	(0.069)	(0.047)	(0.050)	(0.036)
Vector $\mathbf{X}_i$	✓	✓	✓	✓	✓	✓	✓	✓
Attack cluster FEs	✓	✓	✓	✓	✓	✓	✓	✓
GOR FEs		✓	✓		✓	✓		
Extra controls			✓			✓		
Years excluded	2013	2013	2013	2013 & 2014	2013 & 2014	2013 & 2014		
# of attacked districts	30	30	30	16	16	16	43	43
Weight							Year	Quarter
R-squared	0.737	0.749	0.816	0.685	0.698	0.777	0.779	0.787
Observations	350	350	348	364	364	362	337	337

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

[2]The results in this table are robust to using the IV approach, where we instrument contemporary distance with historical (1970-1979) distance to attacks.

A.5 Region exclusion

In this section, we examine the robustness of our results to excluding regions based on geographical boundaries, attack clusters or outliers in the data. First, we drop one GOR at a time, as well as the districts that are not part of the UK mainland (islands), and re-estimate our baseline OLS and IV specifications. We show this exercise graphically in Figure A5, with the OLS results represented on the left panel and the IV results on the right panel. The red vertical line at value -0.022 indicates the magnitude of our baseline estimate of 'Distance' based on the full sample of districts. Each point represents the point estimate of 'Distance' when we remove the districts contained in the region corresponding to the legend below. Thin whiskers from the point estimate are the 95% confidence intervals and fat whiskers are the 90% intervals. The coefficient remains negative throughout, with the effect becoming much stronger when we remove the islands, and statistically less robust when we remove Scotland (even though the coefficient appears to be larger and significant in the IV regressions)[3]. Second, we drop attack clusters one by one. The results are depicted in Figure A6. In every case, our 'Distance' estimate remains negative and statistically significant. As a third and final check, we drop districts that are outliers in terms of their Remain vote. We cut the sample at the top and bottom of the vote share distribution. Our results are reported in Table A4. Once again, we can see that the estimate on 'Distance' remains statistically significant at conventional levels, even if we go as far as excluding the top and bottom 10th percentiles.[4]

A.6 Alternative clustering of errors

Throughout our main analysis, we have clustered the standard errors at the attack cluster level; that is, the level at which the treatment is assigned. In Figure A7, we check the sensitivity of our results to using alternative clustering of errors. The estimate on 'Distance' remains statistically significant, regardless of the clustering method used.

[3]It is worth noting that when we remove Scotland, we exclude one of the most sensationalized attacks in our sample with high media coverage, a fatal outcome and a Muslim perpetrator.

[4]Results from Table A4 and Figure A6 are robust to using the IV approach.

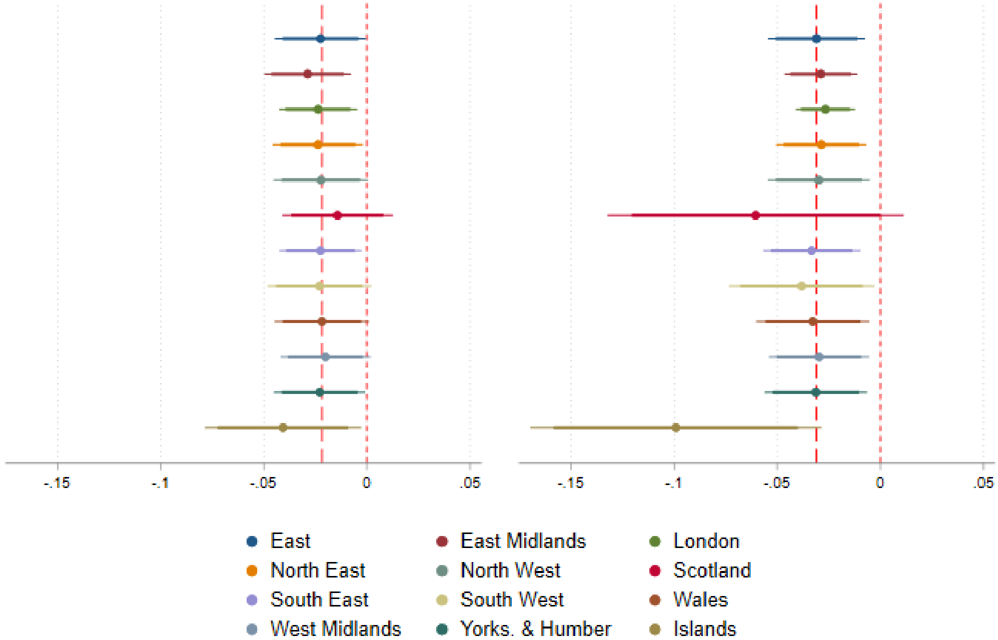

Figure A5: GOR and island exclusion

Notes: Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

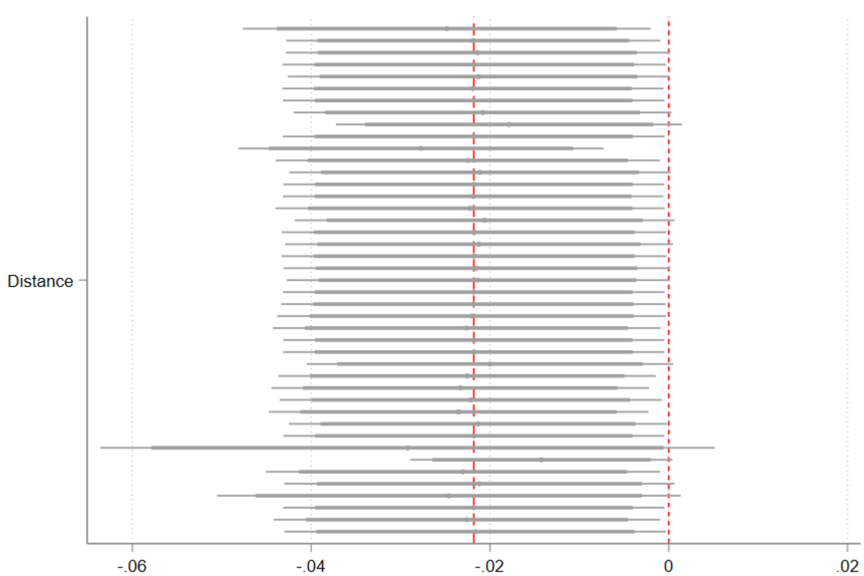

Figure A6: Attack cluster exclusion

Notes: Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

Table A4: Terrorism and the Remain vote:
excluding districts based on vote shares

	(1)	(2)	(3)
Distance	-0.024**	-0.020*	-0.018*
	(0.028)	(0.057)	(0.072)
Vector $\mathbf{X}_i$	✓	✓	✓
Attack cluster FEs	✓	✓	✓
Percentiles excluded	1 & 99	5 & 95	10 & 90
R-squared	0.736	0.722	0.651
Observations	330	305	273

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

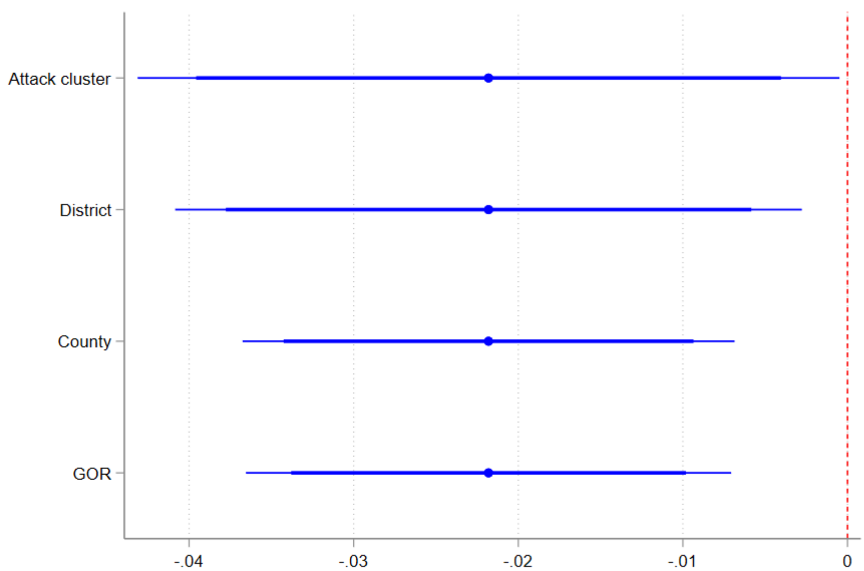

Figure A7: Alternative clustering of errors
Notes: Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

A.7 Additional geography fixed effects

Fixed effects at the level of the closest terrorist-hit district (attack cluster) account for other unobservable characteristics that are shared by geographically close districts. Yet, to allay concerns about residual heterogeneities related to macro-region idiosyncrasies, we augment our baseline model with fixed effects at higher tiers of sub-national division: GORs and countries. The results are presented in Table A5, both before and after the inclusion of attack cluster fixed effects. Across all specifications, the estimate on 'Distance' retains its size and statistical significance.

Table A5: Terrorism and the Remain vote:
additional geography fixed effects

	(1)	(2)	(3)	(4)
Distance	-0.027***	-0.022**	-0.026**	-0.021*
	(0.009)	(0.028)	(0.022)	(0.056)
Vector $\mathbf{X_i}$	✓	✓	✓	✓
GOR FEs	✓		✓	
Country FEs		✓		✓
Attack cluster FEs			✓	✓
R-squared	0.657	0.644	0.766	0.752
Observations	337	337	337	337

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.8 Alternative distance measures

In Table A6, we experiment with alternative measures of distance. In column (1), we employ a categorical variable based on quintile splits of distance within each attack cluster, where category 1 is closest to an attack and category 5 is the furthest away. In column (2), we use the logarithm of distance, whereas, in column (3), we add to the specification the squared value of distance. The results do not change the inferences drawn from earlier findings, and there is no robust evidence of quadratic effects – the estimated coefficient on the squared term is weakly statistically significant and extremely small in magnitude.

Table A6: Terrorism and the Remain vote:
alternative measures of distance

	(1)	(2)	(3)
Distance category (quintile splits)	-0.593*		
	(0.094)		
Ln(1+Distance)		-1.788*	
		(0.056)	
Distance			-0.054**
			(0.045)
Distance squared			0.000*
			(0.069)
Vector $\mathbf{X_i}$	✓	✓	✓
Attack cluster FEs	✓	✓	✓
R-squared	0.751	0.754	0.754
Observations	337	337	337

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.9 Placebo tests

Our results show that proximity to terrorism affects the Remain vote share. To rule out the possibility that this is a spurious relationship, we perform placebo tests where we examine the effects on outcomes that are related to the referendum but should not be affected by distance to terrorism. First, we exploit the results from the 2018 Survation poll on EU matters. Specifically, we use the support for the UK's withdrawal deal in its form at the time of survey (November to December 2018). Second, we use the percentage of invalid votes in the 2016 EU referendum. Third, we employ two measures capturing people's perceptions of the economic consequences of Brexit. To construct these measures, we rely on British Election Study (BES) data for 2016 (wave 8, pre-referendum) and consider individual-level responses to the following question: *"Do you think the following [The general economic situation in the UK / Your personal financial situation] would be better, worse or about the same if the UK leaves the European Union?"*. We match individuals to their local authority district and compute the share of respondents who answered *"Worse"* and *"Much worse"* to the above question. As in Becker et al. (2017), we only keep districts with at least ten respondents. The results from these tests are shown in Table A7. Across all four columns, the estimated coefficient on 'Distance' is very close to 0 and fails to reach statistical significance (as expected).

Table A7: Terrorism and placebo outcomes

	Withdrawal deal support (2018)	Invalid votes (2016)	Economy worse?	Personal finances worse?
	(1)	(2)	(3)	(4)
Distance	0.005	0.000	-0.003	0.014
	(0.169)	(0.308)	(0.829)	(0.479)
Vector $\mathbf{X_i}$	✓	✓	✓	✓
Attack cluster FEs	✓	✓	✓	✓
R-squared	0.673	0.597	0.461	0.302
Observations	337	337	335	335

Notes: Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.10 Within attacked district analysis

Leave and remain votes in the EU referendum at the electoral ward level were made available by Rosenbaum (2017) following a series of Freedom of Information requests to local authorities. This dataset covers 1,261 spatial units in England (13% of the total number of wards in the UK). Exploiting information at such disaggregated level allows us to perform a within attacked district analysis. To do so, we consider 367 wards located in 19 terrorist-hit districts with voting data, and use differences in distances from attacked wards (within these districts) for identification. The core purpose of this exercise is to examine whether the distance-induced Remain effects are also present when we study finer spatial variation, and thus to address concerns of ecological fallacy.[5] A common characteristic of these 19 districts is that they are all urban areas (as classified by the Office for National Statistics), with nearly zero share of rural population (1% or less). Hence, an additional advantage of this exercise is that it can help us ensure that the distance-from-terrorism effects are not simply driven by a rural-urban divide and/or unobserved factors associated with distance from big cities.

To control for other determinants of the Remain vote, we match the ward-level vote shares to cross-sectional data from the 2015 English Index of Multiple Deprivations, as in Becker et al. (2017). This index ranks 32,000 Lower Layer Super Output Areas (LSOAs) in England according to their degree of deprivation across five output areas: income, employment, education and skills, health and crime. We create an average rank of all LSOAs contained within a ward and invert the rank so that higher values represent more deprived wards. We then augment the empirical model of Becker et al. (2017) with our 'Distance' variable, which now captures the distance from the attacked ward within the ward's district.[6] Specifically, our empirical model takes the following form:

$$\text{`Remain'}_s = \theta_0 + \theta_1\text{`Distance'}_{sr} + \theta_2\text{`IMD'}_s + \phi_i^r + \varepsilon_s$$

[5]It must be stressed that, when it comes to the determinants of the Brexit vote, ecological fallacy is of limited concern. See, for example, Alabrese et al. (2019) who show that individual-level regressors give similar results to corresponding aggregate variables at the district (LAD) level.

[6]In some cases, the closest attack is outside the ward's district.

where 'Remain'$_s$ is the Remain vote share in ward s (ranging from 17.5% to 85.6%); 'Distance'$_{sr}$ is the centroid-to-centroid distance in kilometers between ward s and the attacked ward r within the same district i; 'IMD'$_s$ is our standardised index of multiple deprivations; ϕ_i^r represents district fixed effects; and, ε_s is an error term, clustered at the same level. As in our main analysis, we focus on non-attacked wards to address self-selectivity concerns.[7] The inclusion of attacked district fixed effects throughout also ensures that all the residual variation stems from variation across small spatial units within the attacked areas.

The results are presented in Table A8. Column (1) reports the estimates of the above model; columns (2) and (3) add population density and total population, respectively; and column (4) includes all three variables together. Our catch-all measure of deprivation is negatively associated with the Remain vote, as in Becker et al. (2017), whereas population density and total population exert a positive effect on the support for Remain (as expected). Turning now to our variable of interest, 'Distance', we can see that it enters the specification with a negative sign and appears to be statistically significant across all specifications. This is consistent with the findings in our cross-district analysis: proximity to terrorism increases the Remain vote. The estimated coefficient in the most restrictive specification (column (4)) suggests that a 1-km decrease in distance increases the Remain vote share by 0.68 percentage points.

Finally, we take our analysis one step further and explore whether the reported results vary across the 19 terrorist-hit districts depending on their urban sub-classification: 'urban with city and town' (8 districts) versus 'urban with major conurbation' (11 districts). To do so, we augment our regression model with an interaction term between 'Distance' and a binary variable capturing the latter urban sub-category. As shown in columns (5) and (6), the observed effects do not depend on the district's 'conurbation' context: the interaction term fails to reach statistical significance, and its inclusion does not change our results on 'Distance'. This suggests that distance to terrorism matters even when we exploit variation within a continuous network of urban communities, and provides further evidence that our terrorism effects do not reflect proximity-to-big-city effects.

[7] In Bristol, there are 6 attacked wards. We use the distance to the ward that the majority of other wards within that district are closest to. Results are qualitatively the same when we remove Bristol from our sample.

Table A8: Within attacked district analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-1.180***	-0.687*	-1.072**	-0.679*	-1.321**	-0.963*
	(0.007)	(0.052)	(0.024)	(0.072)	(0.034)	(0.082)
IMD: average rank	-3.430***	-4.480***	-5.016***	-5.559***	-3.403***	-5.549***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density		5.952***		5.022***		4.874***
		(0.002)		(0.007)		(0.005)
Population			7.554***	5.920**		6.255**
			(0.005)	(0.032)		(0.021)
Distance x Urban					0.217	0.422
(Major conurbation)					(0.760)	(0.470)
R-squared	0.702	0.742	0.733	0.760	0.703	0.761
Observations	367	367	367	367	367	367

Notes: The dependent variable in all columns is 'Remain'. Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.11 Heterogeneous effects: regressions with interaction terms

In Table A9, we present the results when we augment our baseline model (Eq. (1)) with the interaction term between 'Distance' and the three conditioning binary variables: 'High media coverage', 'Muslim/Jihadi perpetrators' and 'Fatal outcomes'. Columns (1), (3) and (5) report the estimates that are used to calculate the marginal effects in Figure 1, whereas columns (2), (4) and (6) investigate the sensitivity of the results to including the additional controls of Tables 1 and 2. In all cases, the interaction term enters with the appropriate (negative) sign and is highly economically and statistically significant, which confirms that the distance-induced Remain effects depend on the context surrounding the attacks. In Table A9, we also present the results when we run the same regression set-up using 'Turnout' as the dependent variable (columns (7)-(12)). We find no evidence that terrorism induces different turnout rates even when we account for the extent of media coverage, the identity of perpetrators, and the occurrence of fatalities.

Table A9: Terrorism, the Remain vote and turnout: heterogeneous effects

	Remain						Turnout					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Distance	-0.014**	-0.021***	-0.015**	-0.023***	-0.015**	-0.022***	-0.003	-0.005	-0.004	-0.005	-0.004	-0.005
	(0.036)	(0.004)	(0.032)	(0.004)	(0.045)	(0.009)	(0.418)	(0.288)	(0.271)	(0.274)	(0.279)	(0.288)
Distance x High media coverage	-0.047**	-0.045**					-0.005	0.001				
	(0.013)	(0.016)					(0.621)	(0.781)				
Distance x Muslim/Jihadi perpetrators			-0.047***	-0.048***					0.004	0.002		
			(0.002)	(0.001)					(0.459)	(0.635)		
Distance x Fatal outcome					-0.054***	-0.056***					0.003	0.001
					(0.000)	(0.000)					(0.525)	(0.733)
Additional controls?		✓		✓		✓		✓		✓		✓
R-squared	0.755	0.810	0.755	0.810	0.756	0.811	0.835	0.892	0.835	0.892	0.835	0.892
Observations	337	335	337	335	337	335	337	335	337	335	337	335

Notes: The dependent variable in columns (1)-(6) is 'Remain' and the dependent variable in columns (7)-(12) is 'Turnout'. Standard errors are clustered at the level of the closest terrorist-hit district (attack cluster). p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B. Region-Level Analysis: Direct Exposure Effects

B.1 Matching techniques

So far we have studied the spillover effects of terrorism on Remain based on a 'closest attack district' fixed effects strategy. In this section, we consider an alternative approach that allows us to focus on the direct effect of terrorism for the districts that were hit by terrorist attacks. To do so, we compare the average Remain vote share between attacked and non-attacked districts and employ matching techniques to address the endogeneity problem of the terrorism location choice; that is, we match attacked districts with a carefully selected group of non-attacked districts based on a set of observable traits. We rely on coarsened exact matching (CEM).[8] This is a recently developed matching procedure that requires fewer assumptions and possesses more attractive statistical properties than other matching procedures, such as propensity score matching.[9] It also has the advantage that it guarantees a reduction in imbalance after matching. This, however, comes with a cost. Units that cannot be matched are dropped, and thus it typically produces fewer matches than other methods, which can be problematic in finite samples – especially when we match on a large number of variables. To account for this, we focus on the subset of our covariates that can predict the probability of experiencing an attack.

Table B1 reports the results from a linear probability model (LPM), where the dependent variable is a binary indicator coding the districts that were hit by attacks from January 2013 to the referendum date. Column (1) regresses the dependent variable on the variables included in vector $\mathbf{X}_i$, whereas column (2) adds country fixed effects. In line with previous studies (see, for instance, Brodeur, 2018), we find that the most prevalent district-level characteristics influencing the probability of

[8]CEM works by first sorting all the observations into strata, each of which has identical values for all the coarsened pre-treatment covariates, and then discarding all observations within any stratum that does not have at least one observation for each unique value of the treatment variable (Blackwell et al., 2009).

[9]CEM controls not only for covariate imbalance, but also for the degree of model dependence and, more importantly, for the size of estimation error (and statistical bias) in the causal quantity of interest (Iacus et al., 2012). While most matching methods – including propensity score matching – attempt to approximate a classic experiment with complete randomization, CEM approximates the far more efficient randomized block experimental design (King and Nielsen, 2019).

experiencing an attack are crime and past exposure (attack history). However, once we augment the model specification with the set of additional controls discussed in Section 4.2, we can see that population size enters the regressions highly statistically significant and absorbs the impact of the two aforementioned variables (columns (3) and (4)). This implies that terrorist attacks occur more frequently in highly populated areas, and that these areas are also associated with high levels of crime and previous exposure to terrorism.

The treatment effects resulting from the matching procedure are displayed in Table B2. Column (1) performs CEM on attack history, and restricts the matched control observations to come from the same country as the treated observations. Column (2) finds matches using attack history, crime, population size, and population density, whereas column (3) finds matches using the same four covariates but also restricts the matched and control units to come from the same country. The evidence obtained suggests that direct exposure to terrorism increases the Remain vote: in all three specifications, the treatment effect is positive and statistically significant at conventional levels. In addition, comparing the multivariate imbalance measure before and after matching (as captured by the $\mathcal{L}1$ statistic) reveals a substantial reduction in imbalance and a very good match. For instance, in column (3), Greenwich is matched to Redbridge and Ealing, Brighton & Hove is matched to Plymouth, and Denbighshire is matched to Conwy and Isle of Anglesey. All in all, the analysis in this section indicates that districts that experienced an attack are associated with a stronger Remain vote relative to districts that are similar in terms of terrorism determinants but did not experience an attack.

Table B1: Probability of experiencing terrorist attacks

	(1)	(2)	(3)	(4)
Attack history	0.151**	0.152**	0.079	0.079
	(0.017)	(0.016)	(0.153)	(0.151)
Qual. level 4+ share growth	-0.026	-0.023	-0.030	-0.030
	(0.179)	(0.254)	(0.203)	(0.224)
Manufacturing employment share growth	-0.003	-0.005	-0.011	-0.011
	(0.867)	(0.795)	(0.510)	(0.559)
EU accession migrant growth	0.005	0.006	0.015	0.015
	(0.857)	(0.821)	(0.578)	(0.565)
EU 15 migrant growth	-0.033	-0.031	-0.027	-0.027
	(0.298)	(0.341)	(0.399)	(0.397)
Migrants from elsewhere growth	0.054	0.053	0.030	0.029
	(0.172)	(0.186)	(0.467)	(0.475)
Median hourly pay change	0.019	0.016	0.026*	0.026*
	(0.130)	(0.204)	(0.053)	(0.057)
Muslim population growth	0.005	0.003	-0.010	-0.010
	(0.815)	(0.895)	(0.574)	(0.579)
Population density	0.016	0.014	0.004	0.007
	(0.725)	(0.756)	(0.930)	(0.885)
Total crimes and offences	0.049**	0.063**	0.041	0.045
	(0.037)	(0.039)	(0.123)	(0.152)
Total economy EU dependence	0.013	0.022	0.022	0.029
	(0.506)	(0.398)	(0.278)	(0.261)
UKIP support			-0.002	-0.002
			(0.558)	(0.656)
Austerity shock			-0.000	-0.000
			(0.268)	(0.250)
Pensioner share growth			-0.221	-0.218
			(0.422)	(0.431)
Population			0.079***	0.079***
			(0.001)	(0.001)
Twitter usage (75th percentile)			0.021	0.021
			(0.573)	(0.580)
Country FEs		✓		✓
R-squared	0.110	0.113	0.157	0.158
Observations	380	380	378	378

Notes: The dependent variable in all is a binary variable taking value 1 if a district was hit by terrorist attacks between January 2013 and the referendum date. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B2: Direct exposure effects:
coarsened exact matching

	(1)	(2)	(3)
Attacked district	3.696*	5.029*	4.747*
	(0.055)	(0.057)	(0.082)
Pre-matching imbalance	0.173	0.799	0.810
Post-matching imbalance	0.000	0.612	0.516
Strata	5	22	21
R-squared	0.014	0.031	0.035
Observations	377	191	123

Notes: The dependent variable in all columns is 'Remain'. The matching covariates are: 'Attack history' (column (1)) and 'Attack history', 'Total crime and offences', 'Population', and 'Population density' (columns (2) and (3)). In columns (1) and (3), the matched control units are restricted to come from the same country as the treated units. The imbalance measure refers to the multivariate $L1$ imbalance statistic. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.2 Identification tests

The main idea behind our "spillover effect" strategy is that, by excluding the terrorist-hit districts, we can circumvent the issue of endogeneity potentially affecting terrorism locations. One concern associated with this strategy is that the characteristics of a district (which, in turn, may affect the voting behavior of its residents) may be spatially correlated. If, for instance, the same characteristics that affect the probability of a district to experience an attack also affect the probability of the neighbouring districts being attacked, then our estimates may still suffer, to some extent, from selection bias. To address this issue, we present estimates of the LPMs in columns (3) and (4) of Table B1 for the closest non-attacked districts (after excluding the actual attacked districts). The corresponding results, displayed in columns (1) and (2) of Table B3, indicate that the probability of the neighbouring districts being attacked cannot be strongly predicted by any observable characteristics: none of the variables are now statistically significant at the 5% confidence level or higher.

A similar concern may also apply to our IV strategy. If all districts that suffer from terrorist attacks exhibit exactly the same traits, then the factors that drove terrorism activity in the past (and hence the historical distance to attacks) are likely to be the same as those driving terrorism activity today (and hence the contemporary distance to attacks). Columns (3) and (4) of Table B3 reject this argument. Estimating the same LPMs as above but now for the 22 districts that were attacked only in the 1970s – after excluding the 8 districts that were attacked in both periods – shows no strong relationship with any observable 'recent' characteristics, including population density and size.

Table B3: Identification tests

	Closest non-attacked districts		Historical attacked districts	
	(1)	(2)	(3)	(4)
Attack history	-0.040	-0.036		
	(0.463)	(0.512)		
Qual. level 4+ share growth	0.009	0.014	-0.018	-0.013
	(0.743)	(0.616)	(0.256)	(0.420)
Manufacturing employment share growth	-0.018	-0.023	0.024	0.021
	(0.334)	(0.212)	(0.162)	(0.232)
EU accession migrant growth	0.004	0.005	-0.020	-0.018
	(0.887)	(0.845)	(0.329)	(0.380)
EU 15 migrant growth	-0.032	-0.032	0.014	0.014
	(0.309)	(0.305)	(0.730)	(0.731)
Migrants from elsewhere growth	0.024	0.023	0.024	0.022
	(0.519)	(0.557)	(0.331)	(0.375)
Median hourly pay change	0.004	0.001	-0.019*	-0.023*
	(0.761)	(0.931)	(0.088)	(0.056)
Muslim population growth	-0.006	-0.008	-0.008	-0.010
	(0.832)	(0.777)	(0.500)	(0.415)
Population density	0.005	-0.001	-0.034	-0.037
	(0.913)	(0.988)	(0.324)	(0.310)
Total crimes and offences	0.044	0.054*	0.005	0.019
	(0.145)	(0.098)	(0.767)	(0.360)
Total economy EU dependence	-0.038**	-0.045*	0.006	0.009
	(0.046)	(0.072)	(0.671)	(0.663)
UKIP support	0.026	0.031	-0.009	-0.003
	(0.228)	(0.194)	(0.409)	(0.765)
Austerity shock	-0.016	-0.010	-0.024	-0.021
	(0.606)	(0.758)	(0.305)	(0.382)
Pensioner share growth	0.021	0.022	-0.007	-0.007
	(0.383)	(0.365)	(0.764)	(0.780)
Population	0.042*	0.039	0.005	0.003
	(0.081)	(0.114)	(0.731)	(0.855)
Twitter usage (75th percentile)	-0.039	-0.030	0.006	0.014
	(0.359)	(0.484)	(0.870)	(0.714)
Country FEs		✓		✓
R-squared	0.065	0.069	0.038	0.043
Observations	335	335	370	370

Notes: The dependent variable in columns (1) and (2) is a binary variable taking value 1 for the closest non-attacked districts after excluding the actual attacked districts. The dependent variable in columns (3) and (4) is a binary variable taking value 1 if a district was hit by terrorist attacks between 1970 and 1979, after excluding the districts that were also attacked in recent years. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

C. Individual-Level Analysis

C.1 Variable definitions

Table C1 describes all the variables used in the individual-level analysis and provides the corresponding data sources.

Table C1: Variable definitions and data sources for individual-level analysis

Name	Definition	Source
Dependent variable		
Pro-EU	Where an individual places themselves on a 0-10 scale, where 0 is *"Protect our independence"* and 10 is *"Unite fully with the European Union"*	BES waves 8, 12 and 13
Main explanatory variable		
Post-attack	=1 if individual was interviewed after the day of the attack, 0 otherwise	Own calculation from BES waves 8, 12 and 13
Control variables		
Male	=1 if individual is male, 0 otherwise	BES waves 8, 12 and 13
Age	Age of individual	BES waves 8, 12 and 13
Age squared	Age of individual squared	BES waves 8, 12 and 13
Education (low)	=1 if individual's highest qualification is below GCSE, 0 otherwise	BES waves 8, 12 and 13
Education (medium)	=1 if individual has GCSE or A-level as highest qualification, 0 otherwise	BES waves 8, 12 and 13
Education (high)	=1 if individual has undergraduate or postgraduate degree as highest qualification, 0 otherwise	BES waves 8, 12 and 13
Conservative	=1 if individual voted for the Conservative party in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Labour	=1 if individual voted for the Labour party in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Liberal Democrat	=1 if individual voted for the Liberal Democrat party in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
SNP	=1 if individual voted for the SNP in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Plaid Cymru	=1 if individual voted for Plaid Cymru in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
UKIP	=1 if individual voted for UKIP in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Green	=1 if individual voted for the Green party in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Other party	=1 if individual voted for an other party in the 2015 general election, 0 otherwise	BES waves 8, 12 and 13
Other variables		
Terrorism higher?	=1 if individual believes that the threat of terrorism is "Higher" or "Much higher" outside the EU, 0 otherwise ("Lower", "Much lower" and "About the same")	BES waves 8 and 13
Keep nuclear weapons?	=1 if individual believes UK should keep nuclear weapons, 0 otherwise	BES wave 12
Terrorism	=1 if "terrorism" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Immigration	=1 if "immigration" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Health	=1 if "health" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Economy	=1 if "the economy" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Inequality	=1 if "inequality" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Europe	=1 if "Europe" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Negativity	=1 if "negativity" is the most important issue facing the country, 0 otherwise	BES waves 8, 12 and 13
Fight terror vs civil liberty	Where an individual places themselves on a 0-10 scale, where *"Protect civil liberties"* and 10 is *"Fight terrorism"*	BES wave 12

Notes: BES refers to the British Election Study.

C.2 Information on the attacks

In this section, we provide information on the attacks considered in our individual-level analysis: murder of MP Jo Cox (attack #1); Manchester Arena bombing (attack #2); Finsbury Park attack (attack #3). Table C2 reports the date they occurred, the district where they took place, the identity of perpetrator(s), the total number of fatalities and wounded, the BES wave they coincided with, and the timing of each attack in relation to the wave time window. It also provides a link to a BBC article that contains further details on each attack.

Table C2: Information on sampled attacks and corresponding BES waves

Attack	Date	District location	Perpetrator(s) identity	Total fatalities/wounded	BES wave	Days before attack	Days after attack
#1	16th June 2016	Kirklees	Neo-Nazi extremist	1/1	8	42	6
	https://www.bbc.co.uk/news/uk-england-36550304						
#2	22nd May 2017	Manchester	ISIL	23/119	12	11	18
	https://www.bbc.co.uk/news/uk-england-manchester-40008389						
#3	19th June 2017	Islington	Far-right extremist	1/12	13	11	4
	https://www.bbc.co.uk/news/uk-40323769						

Notes: Information on the identity of perpetrator(s) and the number of fatalities and wounded is taken from the Global Terrorism Database. ISIL refers to the Islamic State of Iraq and the Levant.

Our research design assumes that, regardless of where each attack occurred, individuals from all over the UK were potentially exposed to them through media coverage. The three attacks under consideration were, indeed, extensively covered by all national media outlets (newspapers, television, radio, social media platforms), and thus we can safely assume that the individuals in our sample were aware of them in their aftermath. In fact, every major national newspaper covered these attack on their front page the day after they occurred, and stories appeared on front pages many days afterwards. In Figure C1, we provide examples of national newspaper front pages covering the attacks the next day. The fact that they all involved deaths is also an indication of their shock value and amount of reporting.

The INDEPENDENT

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Mark Steel Michael Gove, the new Mr Poverty

Sean O'Grady Goldsmith triumphs – Sir James, that is

Ian Herbert Hodgson's Plan B sinks Bale's Wales

Jo Cox was Labour MP for Batley and Spen in West Yorkshire (Huddersfield Daily Examiner)

Shot dead in the street: MP who lived to serve

EU campaigns suspended as Jo Cox is killed in her constituency

OLIVER WRIGHT
POLITICAL EDITOR

MPs from across the political spectrum last night set aside their differences to pay tribute to one of Parliament's most promising young MPs who was killed in the street. Her suspected killer is a man police are investigating for possible far-right links. Jo Cox, who campaigned to help Syrian refugees, was shot outside her Birstall surgery.

(a) Attack #1

Daily Mail

UNRIVALLED REPORTS & ANALYSIS

65p

Young girls at a pop concert with everything to live for. That's why a fanatic murdered them . . . by SARAH VINE

Georgina, 18, with her pop idol Ariana

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SOLDIERS ON THE STREETS

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Theresa May announced the

(b) Attack #2

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Fresh terror in London as van drives into crowd at mosque

"A group of people quickly started to collect around the assailant. Some tried to hit him, either kicks or punches. By God's grace we manage to surround him and to protect him from any harm. We stopped all forms of attack and abuse towards him that were coming from every angle"

● Man, 47, from south Wales named as suspect
● Imam praised for intervening to keep crowd calm
● Fourth attack to hit UK in last three months

UK yields to EU on first day of Brexit negotiations

Adopted together. Not apart.

ACTION FOR CHILDREN

(c) Attack #3

Figure C1: Newspaper front pages from the day after the attacks

C.3 Covariate balance and matching

Table C3 shows descriptive statistics for the individual-level control variables included in vector $\mathbf{Z}_{nkw}$; namely, gender, age, age squared, level of education (low, medium, high) and the political party for which the interviewee voted in the 2015 general election. For each variable, we report the mean for those interviewed before the attack (control group) and those interviewed after the attack (treatment group) and compute the difference in means across the two groups. We also perform t-tests for differences in means and report the corresponding p-values.

In columns (1)-(4), we have the full sample of respondents across all three waves. The t-test results reveal a strong balance across the two groups for nearly all the pre-treatment attributes. The only characteristic that shows a statistically significant difference across treatment and control units is the low education variable, even though the magnitude of the difference is very small. Because the t-tests for the three indicators of education attainment are not independent of each other, we also perform F-tests of joint significance. To do so, we regress the treatment variable ('Post-attack') on the three education variables and add district-by-wave fixed effects. This F-test returns a p-value of 0.092. In columns (5)-(8), we have the sample of respondents who reside within the counties that were hit by the three attacks. None of the p-values are smaller than 0.05, which indicates a strong balance across the two groups along all pre-treatment attributes. The only variable that appears to be statistically different at the 10% confidence level is the Liberal Democrat vote. However, the F-test of joint significance for the full set of party identification variables yields a p-value of 0.580.

To further support our causal claims – and ensure that these minor differences do not affect our results – we rely on coarsened exact matching (CEM) to pre-process the data and produce covariate balance between the treatment and control groups. In other words, instead of using the full sample of treated and control units, we now match treated units with a carefully selected group of matched control units before comparing their responses to the pro-EU question. Table C4 reports the corresponding results based on three specifications. Column (1) performs CEM on the full set of variables in vector $\mathbf{Z}_{nkw}$; column (2) finds matches using the same variables but also restricts the matched and control units to come from the same survey wave; and column (3) imposes the additional constraint

Table C3: Covariate balance across control and treated units

	All respondents				Respondents within attacked counties			
	Pre-attack mean (1)	Post-attack mean (2)	Difference in means (3)	p-value (4)	Pre-attack mean (5)	Post-attack mean (6)	Difference in means (7)	p-value (8)
Male	0.51	0.50	0.00	0.74	0.49	0.51	-0.02	0.62
Age	55.05	55.07	-0.02	0.90	52.60	53.40	-0.80	0.41
Age squared	3257.37	3267.61	-10.24	0.53	3008.57	3093.81	-85.24	0.38
Education (low)	0.11	0.11	0.01	0.03	0.11	0.10	0.00	0.87
Education (medium)	0.39	0.40	-0.00	0.42	0.39	0.38	0.00	0.94
Education (high)	0.49	0.50	-0.00	0.58	0.51	0.51	-0.01	0.86
Conservative	0.34	0.34	0.00	0.44	0.33	0.30	0.03	0.23
Labour	0.31	0.31	0.00	0.71	0.43	0.41	0.02	0.62
Liberal Democrat	0.09	0.08	0.00	0.30	0.06	0.09	-0.03	0.05
SNP	0.06	0.07	-0.00	0.10	0.00	0.00	0.00	0.62
Plaid Cymru	0.01	0.01	-0.00	0.45				
UKIP	0.13	0.13	-0.00	0.56	0.11	0.13	-0.02	0.34
Green	0.05	0.05	-0.00	0.57	0.05	0.06	-0.01	0.66
Other party	0.01	0.01	-0.00	0.79	0.01	0.01	0.01	0.45
Observations	50,988	11,541	62,529		1,320	330	1,650	

Table C4: Terrorism and pro-EU sentiment: coarsened exact matching

	All respondents			Within attacked counties
	(1)	(2)	(3)	(4)
Post-attack	0.194***	0.117***	0.118**	0.536*
	(0.000)	(0.004)	(0.014)	(0.063)
Pre-matching imbalance	0.163	0.447	0.712	0.687
Post-matching imbalance	0.131	0.218	0.453	0.233
Matched strata	1260	2541	6400	205
R-squared	0.000	0.000	0.000	0.005
Observations	71,744	66,346	42,031	852

Notes: The dependent variable in all columns is 'Pro-EU'. The matching covariates in all columns are the variables in vector $\mathbf{Z}_{nkw}$. In column (2) the matched control units are restricted to come from the same survey wave as the treated units. In column (3) the matched control units are restricted to come from the same survey wave and the same region (GOR) as the treated units. Column (4) performs the CEM of column (2) after restricting the sample to include only individuals living in the counties of the attacks. The imbalance measure refers to the multivariate $L1$ imbalance statistic. Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

that the matched and control units must come from the same region (GOR) too. Finally, column (4) performs the CEM of column (2) after restricting the sample to include only individuals living in the counties of the three terrorist attacks. The evidence obtained is in line with our previous findings. The estimates on ‘Post-attack’ are positive and statistically significant in all specifications, and have similar magnitudes with those reported in Table 4. Overall, the results indicate that: (i) individuals who are exposed to terrorism are more likely to take a positive stance towards the EU compared to individuals who are not exposed to terrorism but are similar across a number of observable characteristics; (ii) this effect is far more pronounced for individuals who are in close proximity to the attacks.

C.4 Results for individual attacks

In Figure C2, we show the results when we estimate our model (Eq. (2)) for each attack/wave separately. We report the estimates of the treatment variable ('Post-attack') for three different specifications: (i) when we regress our outcome variable ('Pro-EU') on the treatment variable alone; (ii) when we add district-by-wave fixed effects; (iii) when we add both district-by-wave fixed effects and the control variables in vector $\mathbf{Z}_{nkw}$. We persistently find a positive effect, suggesting that individuals place themselves closer to the idea of Britain uniting fully with the EU after they are exposed to an attack. As expected, the results are particularly strong and statistically robust for the Manchester Arena bombing (attack #2) which was a highly shocking and sensational event with a large number of casualties (the deadliest attack in the UK since the 2005 London bombings). Front page stories were written about this attack every day up until the London Bridge attack on the 3rd June 2017 (11 days later). Not surprisingly, the estimates appear to be smaller and statistically weaker for the murder of MP Jo Cox (attack #1), which occurred one week before the referendum. Even though this attack received very high media attention the first couple of days after it occurred, its media cycle was relatively short as newspapers and other outlets quickly returned to covering other referendum-related topics (which may have also affected the outcome variable). For example, the attack's last story on the front page of national newspapers was just 3 days after the first reports (ThePaperBoy, 2019). Turning now to the Finsbury Park attack (attack #3), we can observe a strong positive effect on the pro-EU sentiment, which, however, is quite sensitive to the specification used. This is likely an issue of statistical power because the treatment group for this particular attack/wave is quite small – less than 7% of individuals (1,565) were interviewed after the attack – and it becomes even smaller when we add the control variables.

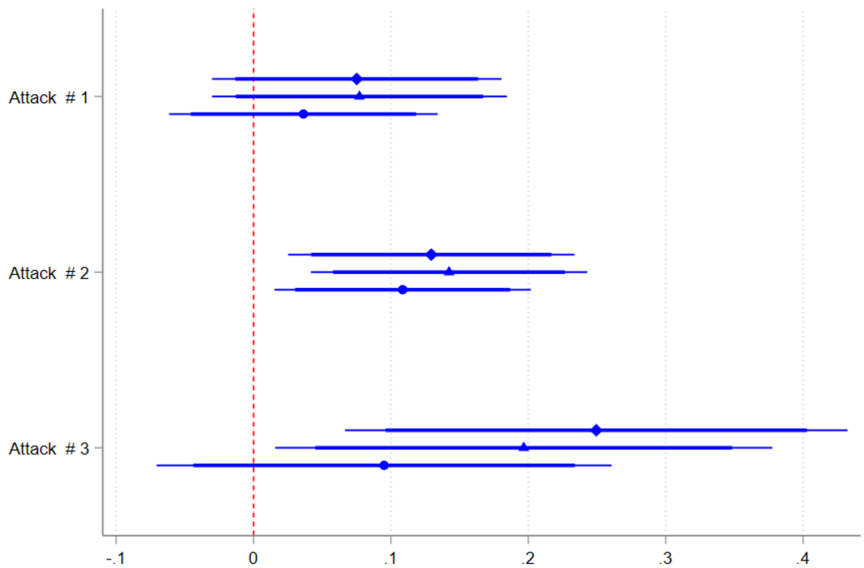

Figure C2: Terrorism and pro-EU sentiment: single attacks

Notes: Specification 1 includes the treatment variable only. Specification 2 includes the treatment variable and district-by-wave FEs. Specification 3 includes the treatment variable, district-by-wave FEs and vector $\mathbf{Z}_{nkw}$. Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

C.5 Alternative clustering of errors

In this section, we test the sensitivity of our results to using alterative clustering of errors. Figure C3 shows how the confidence intervals of the baseline estimate change when the errors are clustered at the level reported on the y-axis. Note that district size corresponds to a set of binary variables based on the quintiles of the district's population, and that clustering at this level accounts for potential over-sampling of larger districts within GORs (Balcells and Torrats-Espinosa, 2018). It is reassuring that regardless of the clustering strategy used, our estimate is highly statistically significant.

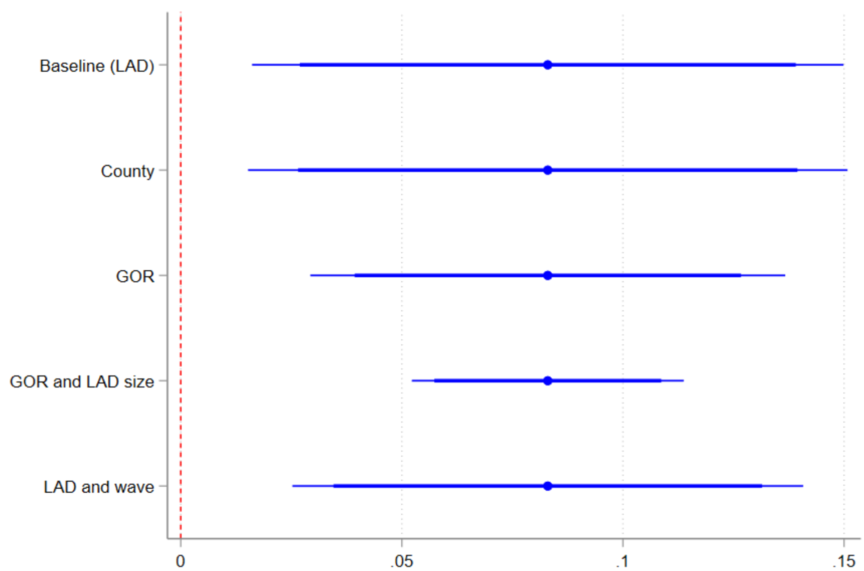

Figure C3: Alternative clustering of errors

Notes: Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

C.6 Difference-in-differences estimation

A potential concern is that our 'Post-attack' estimates capture pre-existing trends in respondents' pro-EU sentiments, which are unrelated to the three terrorist attacks. To address this possibility, we focus on the sub-sample of survey participants who are interviewed twice (once during the attack's survey wave and once more during the previous wave) and replace the outcome variable with its first difference; that is, individuals' responses to the pro-EU question as observed in the attack's wave minus their responses to the same question as observed in the previous wave. This set-up enables accounting for the baseline level of our outcome variable in a difference-in-differences design, and also controls for biases arising from the potential omission of unobserved characteristics (Nussio, 2018). This also means that our estimates can be relatively more conservative as a lot of variation in the outcome variable is absorbed by the 'lagged value'. As shown in Table C5a, the estimates are somewhat smaller that those reported in Table 4 but they still appear to be positive and highly statistically significant, and lead to the same conclusions.[10]

To verify the absence of pre-existing trends, we also perform a placebo test using the 'lagged value' as the outcome variable (see Table C5b). Once we add region-by-wave fixed effects and the variables in vector $\mathbf{Z}_{nkw}$ (columns (2)-(10)), the estimates turn out to be economically and statistically insignificant, and in some cases, have the opposite sign.

C.7 A short-range time window

In this section, we test the sensitivity of our results to using a 3-day time window before and after the attacks; that is, we restrict the sample of treated and control groups to include individuals interviewed within 3 days after the attacks and those interviewed within 3 days before the attacks, respectively. This allows us to substantiate the as-if random treatment assignment assumption and to minimize the

[10]It is worth noting that the disadvantage of using information from previous waves is that the outcome variable becomes more susceptible of being affected by other events (Muñoz et al., 2020), including exposure to past terrorist attacks.

Table C5a: Terrorism and pro-EU sentiment: difference-in-differences estimation

	All respondents							Within attacked counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post-attack	0.053***	0.065***	0.064***	0.067***	0.065***	0.069***	0.067***	0.345**	0.312**	0.340**
	(0.008)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.033)	(0.049)	(0.024)
GOR-by-survey FEs		✓	✓							
County-by-survey FEs				✓	✓					
LAD-by-survey FEs						✓	✓		✓	✓
Vector $\mathbf{Z}_{nkw}$			✓		✓		✓			✓
R-squared	0.000	0.002	0.003	0.003	0.004	0.021	0.025	0.006	0.023	0.035
Observations	55,292	55,292	47,963	55,292	47,963	55,292	47,963	1,436	1,436	1,239
Diff-test								0.030	0.048	0.024

Notes: Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Diff-test reports the p-value of a one-sided test, where H0: the difference in the 'Post-attack' estimates between the sample of attacked counties and the sample of non-attacked counties is equal to zero, and H1: the difference in the estimates between the two samples is positive.

Table C5b: Terrorism and pro-EU sentiment: lagged value as the dependent variable

	All respondents							Within attacked counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post-attack	0.075**	0.020	0.008	0.026	0.007	0.019	-0.007	-0.073	-0.082	-0.040
	(0.050)	(0.636)	(0.830)	(0.534)	(0.858)	(0.649)	(0.853)	(0.741)	(0.669)	(0.837)
GOR-by-survey FEs		✓	✓							
County-by-survey FEs				✓	✓					
LAD-by-survey FEs						✓	✓		✓	✓
Vector $\mathbf{Z}_{nkw}$			✓		✓		✓			✓
R-squared	0.000	0.035	0.324	0.044	0.326	0.077	0.344	0.000	0.069	0.336
Observations	55,292	55,292	47,963	55,292	47,963	55,292	47,963	1,436	1,436	1,239
Diff-test								0.679	0.705	0.439

Notes: Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Diff-test reports the p-value of a one-sided test, where H0: the difference in the 'Post-attack' estimates between the sample of attacked counties and the sample of non-attacked counties is equal to zero, and H1: the difference in the estimates between the two samples is positive.

possibility of other events driving the estimated effects (Nussio et al., 2019). As shown in Figure C4, the treatment effect for the 3-day set-up is almost identical to the one obtained for the full sample (all days). However, as expected, it is less precisely estimated due to the much smaller sample size (lower statistical power), which is one of the downsides of using narrow bandwidths (Muñoz et al., 2020).[11]

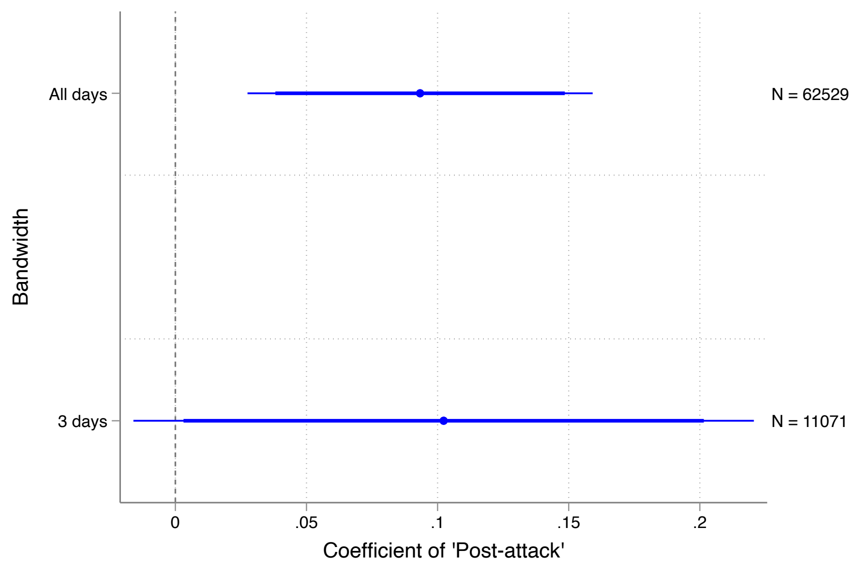

Figure C4: 3-day time window

Notes: Treatment effect for the full sample (all days) and a 3-day bandwidth, based on the specification in column (3) of Table 4. Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

[11] As stressed by Muñoz et al. (2020), individuals interviewed around the day of the event will not necessarily be more similar to each other, and narrower bandwidths will increase variance, but not necessarily reduce bias. In addition, some events can take some time to unfold, and a narrow bandwidth might miss part of the effect.

C.8 Placebo tests

In this section, we perform two placebo tests. The first test considers an unrelated outcome variable: people's positions on whether the UK should keep the nuclear deterrent system, known as Trident. We exploit responses to the question *"Britain should keep its submarines with nuclear weapons"*, which was included in wave 12 only. We code the responses *"Agree"* and *"Strongly agree"* with 1, and all the other responses with 0, and estimate a linear probability model. This is a useful placebo test because a nuclear deterrent is not a suitable tool to prevent, or deter, terrorist attacks. The second test assumes treatment at an arbitrary time point at the left of the cutoff points, as recommended by Muñoz et al. (2020). More precisely, we set the attack dates to be 1 week prior to the actual dates and run the same regression set-up as before (with 'Pro-EU' as the outcome variable). This allows us to further address the possibility of unrelated time trends. The corresponding results are shown in C6. Both placebo tests return (economically and statistically) insignificant coefficients and, as such, provide further credibility to our causal claims.

Table C6: Placebo tests

	Keep nukes?		Pro-EU	
	(1)	(2)	(3)	(4)
Post-attack	-0.009	-0.004		
	(0.214)	(0.510)		
Placebo post-attack			0.010	0.000
			(0.751)	(0.994)
District-by-wave FEs	✓[a]	✓[a]	✓	✓
Vector $\mathbf{Z}_{nkw}$		✓		✓
R-squared	0.059	0.264	0.076	0.336
Observations	19,585	16,915	57,976	49,739

Notes: ✓[a] indicates district FEs (this question was included in one wave only). 'Placebo post-attack' assumes that the attacks occurred 1 week prior to the actual attack dates. Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

C.9 The most important issues facing the country

In this section, we explore the treatment effect on citizens' beliefs about the single most important issue facing the country. We consider 'terrorism' and the six other most popular issues: 'immigration', 'health', 'economy', 'inequality', 'Europe', and 'negativity'. We construct a binary indicator for each one of these issues coding respondents who believe that the corresponding issue is the most important national problem. Columns (1)-(7) of Table C7 show the LPM estimates of the treatment effect on the seven outcome variables. The results indicate that, after a terrorist attack, individuals are 9.3 percentage points more likely to report terrorism as the top national problem. At the same time, we can observe that exposure to terrorism sways public opinion away from all the other issues. Interestingly, after an attack, people seem to perceive 'Europe' as a less important 'problem'.

We also consider an alternative outcome variable, capturing answers to the following question: *"Some people feel that, in order to fight terrorism, we have to accept infringements on privacy and civil liberties, others feel that privacy and civil liberties are to be protected at all cost. Where would you place yourself and the political parties on this scale? [0-10]"*. This question was included in wave 13 only. The variable is re-coded so that higher values represent a greater desire to fight terror and lower values represent a greater desire to protect civil liberties (value 10 corresponds to *"Fight terrorism"* and value 0 corresponds to *"Protect civil liberties"*). The results are displayed in column (8) of Table C7. We find that, after a terrorist attack, individuals are, on average, 0.171 points higher up the scale; that is, they are more willing to give up some liberty to fight terrorism. Taken together, these last rounds of estimates suggest that terrorism displaces attention from other key concerns such as the state of the economy or immigration policies, and increases the perception of insecurity. At the same time, however, terrorism also increases the likelihood that respondents see Remain as a rather safer choice, given the potential security risks of giving up the EU membership.

Table C7: The most important issues facing the country

	Terrorism (1)	Immigration (2)	Health (3)	Economy (4)	Inequality (5)	Europe (6)	Negativity (7)	Fight terror vs civil liberty (8)
Post-attack	0.093***	-0.007*	-0.016***	-0.006**	-0.005**	-0.050***	-0.015***	0.171**
	(0.000)	(0.097)	(0.000)	(0.046)	(0.038)	(0.000)	(0.000)	(0.028)
District-by-wave FEs	✓	✓	✓	✓	✓	✓	✓	✓[a]
Vector $\mathbf{Z}_{nkw}$	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.076	0.179	0.061	0.042	0.061	0.049	0.067	0.214
Observations	59,743	59,743	59,743	59,743	59,743	59,743	59,743	18,006

Notes: ✓[a] indicates district FEs (this question was included in one wave only). Standard errors are clustered at the district level. p-values are reported in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

C.10 The impact of distance

In this section, we examine the conditionality of the treatment effect upon distance to terrorism. To do so, we employ an estimation strategy similar to the one used in other studies on terrorism and voting outcomes (Montalvo, 2011, 2012; Balcells and Torrats-Espinosa, 2018). Specifically, we aggregate the individual-level data to the district level and generate pre- and post-attack district-level observations, and then interact our 'Post-attack' variable with a measure of geographical exposure to terrorism. Our model specification takes the following form:

$$\text{`Pro-EU'}_{piw} = \delta_1\text{`Post-attack'}_{piw} + \delta_2\text{`Post-attack'}_{piw} \times \text{`Distance'}_{iw} + \psi\mathbf{Z}_{piw} + \xi_i + \rho_w + \varepsilon_{piw}$$

where 'Pro-EU'$_{piw}$ is the average value of pro-EU sentiment measured in a given pre/post attack period (with $p = 0$ coding values before the attack and $p = 1$ conding values after the attack) in district i and survey wave w; 'Post-attack'$_{piw}$ is an indicator for whether the outcome is measured before or after the attack; 'Distance'$_{iw}$ is the district i's distance to the terrorist attack in wave w; $\mathbf{Z}_{piw}$ is a vector of control variables (also measured in terms of pre/post attack average values for each district and wave); ξ_i are district fixed effects; ρ_w are wave fixed effects; and, ε_{piw} is an error term.

Using the estimates from the model above, we calculate the margins of the 'Post-attack' variable and plot them over the respective values of the variable 'Distance'. As shown in Figure C5, the treatment effect is highly conditional upon geographic proximity to attacks: while 'Post-attack' exerts a positive and statistically significant effect on the outcome variable at low values of distance, this effect decreases or disappears at high values of distance.[12] Overall, our results in this section confirm that geographic proximity to a terrorist attack can amplify the perception of threat and the personal sense of vulnerability, leading to stronger post-attack reactions.

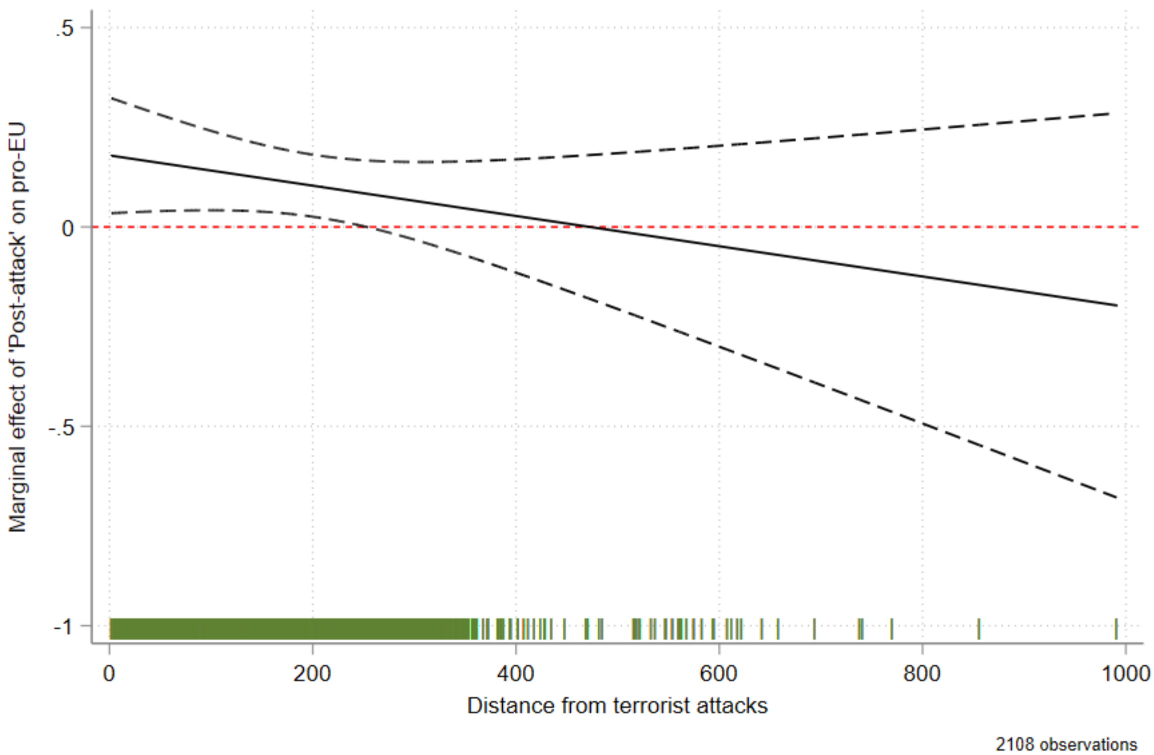

Figure C5: Marginal effects of 'Post-attack'

Notes: Dashed lines signify 95% confidence intervals. Rug plot at horizontal axis illustrates the distribution of distance to the attacked district. Red horizontal line marks marginal effect of 0.

[12]Our results do not change when run the same regression using the first difference in the outcome variable; that is, the average value of pro-EU sentiment measured in a given pre/post attack period minus the corresponding average value in the previous survey wave.

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