Did terrorism affect voting in the Brexit referendum?*

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Abstract

We contribute to the recent research on Brexit and public opinion formation by contending that the determinants of the referendum results should be evaluated against the background of wider public security concerns. Terrorism has long been regarded as a top concern by the British public, more than in any other European country. Terrorist attacks on UK soil raised voters' awareness of security issues and their saliency in the context of an EU referendum. We find that locations affected by terrorist violence in their proximity exhibit an increase in the share of pro-Remain votes, particularly for more sensational attacks. Using individual-level data, we show that in the aftermath of terrorist attacks, citizens are more likely to reconsider the security risks involved in leaving the EU.

Keywords: Brexit, Security, Terrorism, Voting, Referendum

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*We thank Özlem Atikcan, Sarah Brown, Tatiana Coutto, Jessica Di Salvatore, Charlotte Heath-Kelly, Steven McIntosh, Andreas Murr, Enzo Nussio and Sergi Pardos-Prado for helpful comments and suggestions. We are also indebted to the participants of the 44th Symposium of the Spanish Economic Association, and research seminars at the University of Sheffield and the University of Warwick. The usual disclaimer applies.

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1 Introduction

On 23 June 2016, the UK voted to leave the European Union (EU) by 51.89% for Leave to 48.11% for Remain, a margin of 3.78%. The unexpected outcome caught many scholars, pollsters and practitioners by surprise and spurred a growing academic literature on the determinants of the Brexit vote. Socio-economic characteristics enjoy near-consensus support and pro-Leave vote is often explained by financial dissatisfaction, prevalence of national identity, including previous support for UKIP, and social status (see, e.g., Clarke et al., 2017b; Becker et al., 2017; Chan et al., 2017). Older and less educated individuals were also more likely to be pro-Brexit (Chan et al., 2017; Goodwin and Heath, 2016). Furthermore, economic distress in "left behind" areas of globalization and austerity-induced welfare reforms played an important role in the support for the Leave option (Colantone and Stanig, 2018; Fetzer, 2019).

Our article contributes to recent research on Brexit and public opinion formation by contending that the determinants of the referendum results should be also evaluated against the background of wider public security concerns. The United Kingdom has a long history of battling episodes of terrorism and political violence within its borders. In 2015 and 2016 only, 29 terrorist incidents were recorded in the country, excluding Northern Ireland. And in 2017, the year after the Brexit vote, emblematic terrorist attacks, such as those at Westminster Bridge, Manchester Arena and London Bridge, killed a total of 36 people. Not surprisingly, a recent YouGov poll of the public's global concerns shows that international terrorism is regarded by UK citizens as the biggest threat, whereas it is usually economic uncertainty the top problem in other European countries.[1] As of yet, however, extant studies have neglected whether and how security concerns have shaped support for Brexit.

Since 9/11, the social and political implications of terrorism have been active areas of academic debate. Terrorist attacks often receive prominent media coverage and public attention and can affect public attitudes and policy outputs (Legewie, 2013; Neumayer et al., 2014). We claim that terrorist attacks on UK soil raised voters' awareness of security issues and their saliency in the context of an EU referendum. Other studies show that terrorism increases voters' turnout and right-wing votes

[1] Available online: https://tinyurl.com/y96pb48x.

(Balcells and Torrats-Espinosa, 2018; Getmansky and Zeitzoff, 2014; Berrebi and Klor, 2008). We depart from these studies by demonstrating that terrorism does not only affect party preferences, but also public support for broader political and economic issues, such as European integration. At the same time, studies on EU-related referendums show status-quo bias because voters are concerned about drastic economic consequences (Atikcan, 2015), but ignore changes in preferences when voters are cued on potentially drastic public security consequences.

We offer a rigorous empirical analysis that can inform public debates on the impact of security concerns about Brexit and shed light on how political attitudes are formed. The main identifying variation in our analysis is the distance from a terrorist event. For the average terrorist incident, we assume that the effect is a function, *inter alia*, of geographic proximity, the physical distance of an individual from the place where the event occurred. Geographic proximity heightens the perception of threat and affects the extent to which an event is covered by the local media (Böhmelt et al., 2019). Physical proximity to attacks amplifies the personal sense of vulnerability (Braithwaite, 2013), as well as the perception of risk in terms of both the probability and the consequences of terrorist events (Fischhoff et al., 2003). Physical proximity is also shown to increase counterfactual thoughts, i.e., individuals thinking that "they themselves could have suffered from a disaster if the circumstances had been a bit different" (Zagefka, 2018, p.5).

We put forward two competing hypotheses on the impact of terrorism on support for Remain. On one hand, several studies indicate more support for reactionary nationalist, right-wing and anti-immigration parties after terrorism (Legewie, 2013; Berrebi and Klor, 2008; Davis and Deole, 2017). As terrorism can affect anti-foreigner sentiments and increase concerns about less restrictive immigration policies, we expect weaker support for Remain in locations proximate to terrorist attacks. On the other hand, terrorist attacks may expose national security vulnerabilities and increase awareness of the additional security risks of leaving the EU or make citizens more open to EU-wide solutions (Larsen et al., 2019). In a context where terrorism targets other EU countries and media explicitly link terrorism to the risks of Brexit, we can expect voters to react to terrorism by holding onto the status quo. Hence, our second competing hypothesis has it that support for Remain is stronger as distance from terrorist attacks decreases.

We proceed in two steps. First, we exploit data on 380 local authority districts and analyse the spillover effects of terrorism on the Remain vote. To do so, we employ a closest terrorist-hit district fixed effects strategy, where we use differences in distances from the same neighbouring attacked district as a the identifying source of variation in terrorism exposure. We find support for the hypothesis that terrorism increases the share of votes in favor of the EU. In our most conservative estimate, we show that two non-attacked districts – within the same attack cluster – that differ by 45 kms in terms of proximity to the attacked district are expected to differ by 1 percentage point in terms of support for Remain. We also show that the distance-induced Remain effects persist when we instrument contemporary distance with historical distance from terrorism, when we study within attacked district variation using data at the electoral ward level, and when we perform a series of robustness checks. Finally, we explore the conditionality of the effects upon the context surrounding the attacks, throwing light on possible mediating factors. We find that proximity to terrorism has a much stronger effect on the Remain vote when the attacks attracted prominent national media coverage, when they caused casualties and when they involved Muslim or Jihadist perpetrators.

In the second step, we turn to individual-level data from the British Election Study. This data allows us to provide further insights into the mechanisms behind our district-level results but also to substantiate our causal claims. To this end, we employ a quasi-experimental design that exploits the occurrence of an unexpected event (terrorism) during the fieldwork of a survey to assign respondents into treatment and control groups as good as randomly (Balcells and Torrats-Espinosa, 2018). We find that, in the wake of terrorist attacks, individuals are more likely to report positive attitudes about the EU and to perceive higher risks of terrorism if the UK leaves the EU. In line with our district-level results, we also find that these effects are much stronger for individuals living in the counties of the terrorist attacks. To lend further credibility to the causal estimates, we implement Muñoz et al. (2020)'s best practices in the form of alternative estimation strategies and robustness checks – such as controlling for the baseline level of our outcome variable, using matching techniques to ensure covariate balance, and testing for unrelated time trends – and our conclusions do not change.

2 Theory

In recent years, a growing literature has pointed to the adverse effects of terrorist violence on political trust and attitudes as well as on individual behavior (Birkelund et al., 2019). The main political consequences of terrorism observed across studies are related to a rallying around the flag dynamic, with increased approval of presidents and trust in government, nationalist votes and turnout (Dinesen and Jæger, 2013; Getmansky and Zeitzoff, 2014; Balcells and Torrats-Espinosa, 2018). Terrorism reinforces hardline beliefs and may trigger hostility against immigrants, even when the threat is just perceived (Huddy et al., 2005; Legewie, 2013; Nussio et al., 2019).

The link between terrorism and migration has become increasingly common in the political discourse within the EU. Despite the lack of evidence to support an objective association between migration and terrorism, strict immigration policies are often justified as a response to the threat of transnational terrorism that allegedly operates and infiltrates migration flows (Bove and Böhmelt, 2016; Bove et al., 2020). Within the EU, negative attitudes towards immigrants are also associated with higher levels of euroskepticism because the abolition of borders and free movement of people increase feelings of exposure to security threats and terrorism (McLaren, 2002). The Leave campaign's narrative revolving around the idea of "taking back control" included immigration issues, often framed in relation to generous fiscal transfers. References to the threat posed by a borderless Europe, however, were also abundant. Leave campaigners highlighted that as an EU member, the UK has lost control over national borders and is powerless against terrorist threats; the mere membership to the EU, they argued, is a sign that welcomes terrorists to Europe.[2]

As such, terrorist attacks can increase support for Brexit through a rally-around-the-flag effect. Terrorist attacks foster nationalist and patriotic feelings by reinforcing in-group social cohesion. As a consequence, voters are expected to be more supportive of the UK allegedly re-gaining independence from the EU. Furthermore, feelings of fear and anxiety in the aftermath of terrorism, reinforce in-group cohesion at the expense of out-groups, thus further reducing support for the EU and its communitarian policies. As a result, support for Remain decreases. The rally-around-the-flag effect

[2] http://www.voteleavetakecontrol.org/briefing_safety.html

is expected to unfold the closer voters are to terrorist attacks. These arguments lead to the following hypothesis:

H1a: Proximity to terrorism decreases support for Remain

From a psychological perspective, the implications of terrorism and other violent events on individuals are not always primarily negative. In their review of the topic, Vázquez et al. (2008, p. 70) conclude that "terrorist attacks – originally planned to weaken society – can sometimes act as catalysts to develop strengths related to human relations, to improve social and community aspects, and even philosophical or spiritual aspects". While terrorist attacks do positively affect national pride and intra-group cohesion, this is not necessarily accompanied by more negative world-views, e.g., trust for other people. More importantly, a sense of community and solidarity are among the most common positive feelings reported after a terrorist attack (Vázquez et al., 2008). And in a recent study, Larsen et al. (2019) find that, after the 2016 Berlin attack, people in Germany held more positive attitudes towards the EU and did not change their feelings about immigrants and refugees. One suggested mechanism is more openness to EU-wide solutions. Furthermore, the political context also influences emotional responses to terrorism. According to Huddy and Feldman (2011), anger leads to reduced risk perception, more aggressive responses and more risk-taking in order to change a situation; conversely, anxiety results in overestimation of threats and careful, systematic information processing, thus a general preference for status quo.

Exposure to terrorism increases stress, fear, and anxiety in the population (Huddy et al., 2005), and, in fact, terrorism in Europe seems to have mostly spurred anxiety rather than anger. Rather than a vengeance rhetoric, terrorist attacks in Paris have been followed by calls to "go about normal life" as an act of resistance against terrorism (Browning, 2018). Similarly, following the attacks in London and the media depiction of a nation still "reeling" from the Manchester Arena bombing and "under siege", social media users from the UK were outraged by such coverage and replied by resuming the World War II slogan of "Keep Calm and Carry On". And research in neuropsychology suggests that anxiety and fear result in greater risk aversion and increase in the use of reason, information search and reflective judgement (e.g., Marcus et al., 2000). In the context of the Irish referendum on the "Fiscal Compact" treaty, Garry (2014) shows that anxious and fearful citizens were more likely than angry citizens to learn about the substantive content of the treaty, reflect upon it and vote on the basis of its implications. Whereas anger affected support for the 'risky' referendum option, anxiety affected support for the option framed as 'non-risky'. "The great struggle was between fear and anger – and fear won" (Irish Times, 02/06/2012, also cited in Garry (2014)). Independence referendums, such as the 2014 referendum on Scottish independence, offer particularly uncertain choices with high stakes, and Liñeira and Henderson (2019) find that, faced with uncertainty, risk-averse voters prevent losses by voting against change. As such, risk attitudes play a particularly important role for vote choice.

Early in the Brexit campaign, the Remain camp had three core arguments, that remaining would be better for the economy, security and UK's place in the world. In fact, the Remain camp made the explicit argument that the UK would be more secure inside the EU, because the EU gives effective tools to fight common threats, such as terrorism and global warming. A main concern was Britain losing access to EU databases on border crossings and police stops (used to track terrorists), which increased significantly after the spate of terrorist attacks in 2015.[3] David Cameron himself asserted that EU membership made Britain safer, hinted that Brexit might increase the risk of conflict and even said that the so-called Islamic State would be pleased if the UK left the EU.[4] In a similar vein, prominent policymakers, such as the former heads of GCHQ, MI5 and MI6, the former director of CIA David Petraeus, the head of Europol, the Defence secretary, Michael Fallon and other leading figures, suggested that leaving would present real risks to security and counter-terrorism efforts.[5]

And although the Remain camp's message became more focused on economic concerns as the campaign unfolded, using novel survey data Atikcan et al. (2020) show that 43% of the Remain supporters cited the UK's ability – as an EU member – to fight more effectively against terrorism to justify their choice. And perhaps more importantly, the media significantly contributed to reinforcing

[3]By one estimate, British law enforcement officials consulted the Schengen Information System, 539 million times in 2017. Available online at: https://tinyurl.com/y6kdedyu.

[4]Available online at: https://tinyurl.com/yxkzyhgp, https://tinyurl.com/yxrkcg24

[5]Available online at: https://tinyurl.com/y63t3oww

the link between the UK public security and the key role of the EU as a security provider. Since the 2004 bombings of commuter trains in Madrid, the number of Jihadist terrorist attacks has increased in Europe, leading to growing concerns about the security of targeted countries. Regardless of their initial attitude towards Europe, terrorism might make voters more concerned with the issue of security and more aware that this is important to them, or make them change their opinion of Europe as a provider of security. Consistent with feelings of anxiety pushing people to re-assess and carefully evaluate information, Goodwin et al. (2020) show that voters' familiarity with Eurosceptic arguments reduced the influence of the latter and in favor of less familiar pro-EU ones, which were more likely to shape voting decisions. Fighting terrorism was one of the less familiar but highly-prominent arguments, particularly for those living nearby targeted areas. Atikcan et al. (2020) note that the case of Brexit distances itself from other EU or independence referendums in which highly risky economic consequences of change pushed people to vote in favor of the status quo. We argue that in the aftermath of terrorist attacks, citizens become more aware of the saliency of security and terrorism and reconsider the security risks involved in leaving the EU. As in the case of risky economic consequences generating a pro-status quo bias, terrorism may result in a similar change in preferences towards a seemingly less risky option, namely to Remain. This would also explain why voters do not punish incumbents after terrorist events, but they rather support them and the status quo "as a way to confront terrorists" (Balcells and Torrats-Espinosa, 2018). Consistent with this discussion, we formulate a countervailing hypothesis as follows:

H1b: Proximity to terrorism increases support for Remain

Before turning to the empirical analysis, we provide information about the data and variables, and some institutional context of the Brexit vote and background material on terrorism in the UK.

3 Region-Level Analysis: Data and Variables

Dependent variable: Remain votes

Figure A.1 in the Appendix presents a map of the support for the Remain side across local authority districts. We use the percentage of votes for Remain at the district level from the Electoral Commission, and then complement this information with data at ward level from Rosenbaum (2017).

Main explanatory variable: terrorism

Data on terrorism are taken from the Global Terrorism Database (GTD). Terrorism is defined as "the premeditated use or threat to use violence by individuals or sub-national groups against noncombatants in order to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims" (Enders et al., 2011, p.321). We choose a relatively wide window and consider all terrorist attacks from January 2013 to 23 June 2016. January 2013 is a representative month as David Cameron first mentioned the EU referendum on 23rd January 2013.[6] And since the announcement was made, the public debate increasingly revolved around the issue of the costs and benefits of leaving the EU.[7] At the same time, 2013 saw a sharp increase in the frequency of terrorist attacks in the country (see Figure A.2 in the Appendix). Given the likely stronger impact of most recent episodes, we also run models where we weight our coefficients by the time since the last episode of terrorism.

In Figure A.3 of the Appendix, we present a map of terrorist incidents in the UK from January 2013 to the referendum date. There are a total of 43 districts targeted by terrorist violence, and, not surprisingly, London is the city with most incidents. Yet, attacks are scattered around the country, and even if terrorism *per se* is a rather rare event for the average district, all districts are exposed to neighbors' attacks. A string of terrorist attacks has hit the country in recent years. Among the most emblematic attacks before the Brexit vote, there is the assassination of Jo Cox (June 2016),

[6] Available online at: https://www.bbc.co.uk/news/uk-politics-21148282

[7] Available online at: https://tinyurl.com/yxnmogdf

a member of parliament who campaigned against a British exit. In December 2015, three people were stabbed in east London by an attacker driven by Islamic extremism. In February 2014, the New Irish Republican Army (NIRA) claimed responsibility for a series of parcel bombs sent to army recruitment offices in at least seven cities or towns in England. In May 2013, a British soldier, Lee Rigby, was murdered in an attack in Woolwich by two Islamist extremists. Not surprisingly, after the series of attacks around the country in recent years, the number of terrorism-related arrests in Britain hit a record high, with 441 people held on suspicion of terrorism-related activity as of March 2018.[8] And, as noted above, terrorism is becoming an increasing concern for the British public.

Control variables

Following the existing literature on the determinants of the Brexit vote (Becker et al., 2017; Goodwin and Milazzo, 2017; Clarke et al., 2017a; Chan et al., 2017; Colantone and Stanig, 2018; Pickard, 2019), we control for a broad set of variables that may confound the relationship between terrorism and the referendum returns. As in prior studies, we link data from the 2001 and 2011 censuses using changes and growth rates to capture changing trends. In particular, to account for the impact of education attainment on vote choice, we control for the growth in the share of the highly educated population, defined as the share of citizens with an undergraduate degree, professional qualification or equivalent. To capture the important role played by immigration in predicting the referendum outcomes, we include growth rates in the local population shares by three immigration origin groups: the 15 'old' EU member states, the 12 states that joined the EU in 2004 and 2007, and non-EU countries. To address the claim that the Leave campaign resonated particularly well with voters in areas that had experienced prolonged economic downturn (Becker et al., 2017), we control for the change in the share of the population that are employed in the manufacturing sector, and the change in the median hourly pay. We also add to the specification the share of value added in a UK region that can be attributed to consumption and investment demand in the rest of the EU as a proxy for 'globalization' and 'EU trade integration', and the change in the share of Muslim population to capture

[8] Available online at: `https://tinyurl.com/ydgn8coj`

changing trends in the district's religious diversity. Finally, we include a set of variables that are potentially correlated with terrorism exposure, but may also be relevant for explaining the referendum outcomes (see, e.g., Marineau et al., 2018). Specifically, we control for population density, a measure of crime (the logarithm of the district's total number of crimes and offences) and a measure of attack history (a binary indicator coding districts that experienced terrorist attacks between January 1996 and December 2012). Further discussion on the choice of control variables, and a full description of all variables used in the regional-level analysis (together with the corresponding data sources), are provided in Section A.1 of the Appendix.

4 Region-Level Analysis: Empirical Design and Findings

4.1 Methodology

To test our hypotheses, we employ data at the local authority district (LAD) level – which comprises 380 spatial units across England, Scotland and Wales. Our estimation strategy exploits the fact that only 11% of these districts were hit by terrorist attacks over the sampled period, and uses the distance of non-attacked districts from their closest attacked district as the identifying source of variation. The idea behind this method is that, by focusing on 'spillover effects' rather than direct exposure effects, we can address self-selectivity concerns (Bratti et al., 2017); that is, unobserved factors – that are not fully captured by our covariates – affecting both the likelihood of a district to experience terrorist attacks and the voting behavior of its residents. Specifically, our empirical model takes the following form:

$$\text{`Remain'}_i = \beta_0 + \beta_1 \text{`Distance'}_{ij} + \beta_2 \mathbf{X}_i + \mu_c^j + \varepsilon_i \tag{1}$$

where 'Remain'$_i$ is the Remain vote share in district i (ranging from 24.4% to 78.6%); 'Distance'$_{ij}$ is the centroid-to-centroid distance in kilometers between district i and the closest terrorist-hit district j; $\mathbf{X}_i$ is a vector of district i's covariates; μ_c^j represents fixed effects at the attack cluster level c, with each cluster consisting of all districts with the same closest terrorist-hit district j (43 clusters in total); and, ε_i is an error term, clustered at the same level. Our parameter of interest, β_1, measures the effect of proximity to terrorism on the Remain vote, with a positive value supporting *H1a*, i.e., proximity to terrorism decreases support for Remain, and a negative value supporting *H1b*. Under this setting, the key identification assumption is that the occurrence of a terrorist attack in district j is not correlated with unobserved determinants of the Remain vote in district i, where $i \neq j$.[9]

$\mathbf{X}_i$ includes the control variables described in Section 3. As already mentioned, these variables can serve as potential predictors of the likelihood to experience terrorism or have been identified as significant correlates of the Brexit referendum returns in prior studies. However, to strengthen our identification assumption, we also experiment by adding a wide range of additional observable characteristics at the district i level. Furthermore, to account for residual heterogeneities related to macro-region idiosyncrasies, we augment Eq. (1) with fixed effects at higher tiers of sub-national division: countries and government office regions (GORs).[10] Finally, we report instrumental variable (IV) estimates of Eq. (1), where 'Distance'$_{ij}$ is instrumented through 'historical' distance from terrorism, and perform a series of robustness and sensitivity checks, including a within attacked district analysis.

4.2 Main results

Table 1 shows our main results.[11] Column (1) reports the estimates of Eq. (1) based on the baseline working sample of non-attacked districts, and provides strong evidence in favor of *H1b*. In particular, we observe a negative (positive) and highly statistically significant effect of distance (proximity) from terrorism on support for Remain, where a 1-km decrease in distance increases the Remain vote share by 0.022 percentage points. This effect is substantively non-negligible: two non-attacked

[9] 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. In Section B.2 of the Appendix, we show that the probability of the neighbouring districts being attacked cannot be significantly predicted by any observable characteristics (after excluding the actual attacked districts).

[10] England, Scotland and Wales (countries) are divided into 11 GORs.

[11] In Section A.3 of the Appendix, we report the results of the full set of variables included in vector $\mathbf{X}_i$.

districts – within the same attack cluster – that differ by 45 kms in terms of proximity to the attacked district are expected to differ by 1 percentage point in terms of support for Remain. In columns (2)-(7), we augment the specification of column (1) with additional district-level controls, which are first introduced separately and then jointly. In line with arguments presented in the relevant literature (Becker et al., 2017; Chan et al., 2017; Fetzer, 2019), we include the pre-referendum share of UKIP supporters ('UKIP'), the extent of total fiscal cuts over the period 2010-2015 ('Austerity shock'), the growth rate in the share of the population aged 60 or older ('Pensioner share growth'), and the district's total population ('Population'). To capture the impact of social media on political attitudes we also include a binary indicator for districts with high Twitter usage per capita ('Twitter usage'). The effect of distance remains negative, statistically significant, and stable in size across specifications. Some of these controls are plausibly post-treatment (such as the UKIP support) and the inclusion of a large number of covariates can introduce multicollinearity problems (Colantone and Stanig, 2018). However, the low sensitivity of our distance estimates in columns (2)-(7) is quite reassuring as regards to biases arising from the potential omission of unobserved characteristics.

One potential explanation for the aforementioned results is that terrorism changes the composition of the electorate. If, for instance, proximity to terrorism increases the likelihood that public attitudes are translated into votes, then the positive Remain effects may be driven by higher post-treatment mobilization of the Remain supporters. To examine this possibility, we replace the dependent variable with districts' turnout rate ('Turnout')[12] and run the same regression set-up as in Table 1. The corresponding results, reported in Table 2, indicate that proximity to terrorism does not induce different turnout rates. As one would expect given its salience, being closer to terrorist-hit districts is associated with higher voter mobilization, and therefore the estimate on distance is negative, yet the effect is substantively small and fails to reach statistical significance in all specifications. Controlling for turnout rates in the regressions for 'Remain' has also little impact on the estimates reported in Table 1 (results available in Section A.3 of the Appendix).

To corroborate our identification strategy, we re-estimate our model using IV techniques. Moti-

[12]Figure A.4 in the Appendix provides a map with the turnout rates across districts (LADs).

vated by earlier studies, we instrument distance from recent attacks using 'historical' distance from attacks (for a recent application, see Wahl, 2017); that is, the geodesic distance of a non-attacked district from the closest district that was hit by terrorism over the period 1970-1979 (the first 10 years for which data on terrorism are available in the GTD). Since our historical distance measure refers to 30 attacks that occurred about four decades before the referendum, it is expected to influence the Remain vote indirectly through correlation with distance from future attacks.[13] Table 3 shows the corresponding results. Column (1) reports the estimates for the baseline specification, whereas column (2) shows robustness to introducing additional covariates. The first-stage coefficient on the instrument is positive and statistically significant at the 1% confidence level across all four columns. The F-test of excluded instruments also produces a very high F-statistic, documenting the strength of the instrument. Turning now to the second stage results, we can see that the magnitude of the coefficient on distance is relatively close to the OLS one (reported in Table 1), pointing to the absence of a strong endogeneity bias. Running the same IV regressions for 'Turnout' provides evidence that proximity to terrorism leads to statistically higher turnout rates, even though the effect is again substantively small (columns (3)-(4)).

Robustness

In the Appendix, we perform various tests to assess the robustness of our key findings. Specifically, we examine the sensitivity of our estimates to controlling for a broad set of additional district-level covariates (Section A.3), 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 (Section A.4), to excluding regions (Section A.5), and to using alternative clustering of errors (Section A.6). Furthermore, we check whether our results hold when we introduce fixed effects at higher tiers of sub-national division (Section A.7) and when we employ categorical or non-linear measures of distance (Section A.8). In all cases, distance from terrorism has a negative and statistically significant

[13] 22 out of the 30 'historical' attacked districts were attacked only in the 1970s (and not in recent years). In Section B.2 of the Appendix, we show that the probability of these 22 districts being attacked cannot be explained by any observable 'recent' characteristics, including population density and size.

effect on the Remain vote, providing further support for *H1b*. To rule out the possibility of a spurious relationship (or that our estimates are driven by unobserved factors associated with other type of distances), we also perform placebo tests where we examine the effects on outcomes that are related to the referendum but should not be affected by distance from terrorism, such as people's perceptions of the economic consequences of Brexit. None of the placebo tests return statistically significant estimates, confirming the validity of our results (Section A.9).

Even though the official referendum results were published at the district (LAD) level, voting data at the level of electoral wards can also be obtained from Rosenbaum (2017). Unfortunately, this dataset covers only 13% of the total number of wards in the UK and information on a wide range of socio-economic characteristics at such disaggregated level is not available. Yet, this dataset allows us to test whether our results persist when we focus on variation within attacked districts, and to address concerns of ecological fallacy. To this end, we consider 367 wards located in 19 terrorist-hit districts with data on the referendum results, and use differences in distances from attacked wards (within these districts) for identification. We also control for wards' degree of deprivation (composed of deprivation indices covering income, employment, education and skills, health and crime), as well as their population density and size, and add attacked-district fixed effects to capture unobserved characteristics that are shared by geographically close wards. The estimates obtained do not change the inferences drawn from the cross-district analysis: once again, we find that proximity to terrorism increases the Remain vote. Since all 19 districts are classified as urban areas (with most of them having major conurbation), these within-district results also provide further evidence that our terrorism effects do not reflect proximity-to-big-city effects. We refer to Section A.10 of the Appendix for a full discussion of the ward-level analysis.

4.3 Heterogeneous effects

The media are primarily responsible for providing information to the public in the aftermath of terrorist events, but they also can shape the salience of national rhetoric and reinforce the perception of threat (Hopkins, 2010). The amount of reporting can thus be seen as a reflection of the event's relevance and national importance (Legewie, 2013). Following these arguments, we expect our results to be much stronger for attacks that attracted prominent media attention. To test for this, we augment Eq. (1) with an interaction term between distance and a measure of media reporting of the attack(s) occurred in the closest terrorist-hit district. We focus on newspaper reporting for which data can be extracted from LexisNexis: an online service that searches through the text of thousands of news publications. For the purpose of this study, we limit the search results to national newspapers from UK-based sources that include the term 'terrorism' or 'terrorist', the location, and other key words related to each attack, in the month following the attack. We then construct a proxy for high media coverage using the attacks with 10 or more LexisNexis hits (relevant articles),[14] corresponding to nearly half of the attack clusters in our sample (20 out of 43). Panel (a) of Figure 1 displays the marginal effects of 'Distance' at values 0 and 1 of 'High Media Coverage'. The evidence obtained confirms that media coverage plays an important role in moderating the effect of distance on the Remain vote: when the attacks are extensively covered by media, the corresponding estimate is four times as large.

Domestic terrorism is often portrayed as a minor threat committed by troubled, mentally ill loners, whereas terrorism motivated by radical interpretation of Islam is framed as a hostile external force (Powell, 2011). At the same time, when people are killed in an attack, the shock value and the fear of terrorism are amplified (Zhang et al., 2013). To examine whether our results change when we focus on attacks with Muslim/Jihadist perpetrators or those that involved deaths, we employ the same framework as in the previous paragraph and introduce interaction terms between distance and indicators capturing the occurrence of these types of attacks in the closest terrorist-hit district (5 cases with Muslim/Jihadist perpetrators and 5 cases with fatal outcomes). The corresponding marginal effects, reported in panels (b) and (c) of Figure 1, confirm that proximity to terrorism has a more pronounced positive effect on the Remain vote when the perpetrators are members of an out-group or an external military movement, and when the attacks involve deaths.

Due to high correlation between the three conditioning factors, one has to be very cautious in

[14] A binary indicator is less sensitive to outliers than a continuous measure and reduces the noise from not considering information from other media outlets.

prioritizing and uncovering links among them. Nevertheless, the analysis in this section clearly indicates that our findings are stronger for attacks that are deemed more relevant than others either due to their media attention-grabbing nature or their 'perceived' potential to be a national security threat.[15]

4.4 Direct exposure effects

An alternative way to answer our research question is to focus on the direct effect of terrorism on the Remain vote for the districts that were hit by terrorist attacks. Based on our results so far, this approach is likely to produce biased estimates due to the existence of spillover effects on the neighbouring districts. We do expect, however, that attacked districts will have a higher (on average) Remain vote share than the rest of the districts when the full sample of districts is taken into account. In Section B.1 of the Appendix, we perform an analysis along these lines and use matching techniques to address the endogeneity problem of the terrorism location choice. Specifically, we estimate the effect of terrorism as the difference in the sample average of the Remain vote between treated observations and a group of matched control observations, which are carefully selected based on coarsened exact matching (Iacus et al., 2012). To do that, we first identify the most prevalent district-level characteristics influencing the probability to experience a terrorist attack. We find that districts with high levels of crime and history of attacks (which also tend to be more populated areas) are more likely to be hit by terrorism. We then match attacked districts with non-attacked districts based on these characteristics. The results confirm that districts that experienced an attack are indeed associated with a stronger Remain vote relative to districts that are similar in terms of terrorism determinants but did not experience an attack. If anything, this approach increases our confidence in our main finding: terrorism is associated with increased support for Remain.

[15] In Section A.11 of the Appendix, we present the results of this section for both the Remain vote and the turnout rate, and explore their robustness to including the additional controls of Tables 1 and 2.

5 Individual-Level Analysis

5.1 Data and methodology

To shed light into the micro-foundations underlying the terrorism-induced Remain effects at the regional-level, we use individual-level data from the British Election Study (BES). Exploiting information from the survey waves that coincide with terrorist attacks allows us to examine the causal effect of terrorism on people's responses. Our identification strategy relies on the assumption that the timing of attacks is exogenous relative to that of the interviews, and thus individuals interviewed after the attack can be defined as the 'treatment' group whereas those interviewed before the attack can be defined as the 'control' group (Muñoz et al., 2020; Balcells and Torrats-Espinosa, 2018).

We consider three of the five 'major' terrorist attacks that occurred in 2016 and 2017:[16] the murder of MP Jo Cox (16 June 2016); the Manchester Arena bombing (22 May 2017); and the Finsbury Park attack (19 June 2017). The rationale for the choice of these attacks is twofold: first, they all received widespread media coverage and resulted in deaths, which makes them particularly impactful and relevant; and second, they overlapped with recent BES waves (8, 12 and 13, respectively) containing comparable information on attitudes and perceptions about the EU.[17] In particular, we infer individuals' pro-EU sentiment from their answer to the following question, which is worded in exactly the same way across the three waves: *"Some people feel that Britain should do all it can to unite fully with the EU. Other people feel that Britain should do all it can to protect its independence from the EU. Where would you place yourself on a 0-10 scale?"* (with higher values indicating more positive attitudes about the EU). We then estimate the causal effect of terrorist attacks on EU attitudes

[16]The two other 'major' attacks are the Westminster Bridge attack (22 March 2017) and the London Bridge attack (3 June 2017). We do not consider the former since its timing did not coincide with the timing of BES waves. We also do not consider the latter since it occurred towards the end of wave 12. Moreover, the Manchester Arena bombing (wave 12) took place 11 days earlier, and thus the individuals interviewed between the two attacks are already defined as 'treated'.

[17]In Section C.2 of the Appendix, we provide additional information on these attacks. To show that the individuals in our sample were aware of these attacks, we also provide examples of national newspaper front pages covering the attacks the day after they occurred.

using the following model (see also Balcells and Torrats-Espinosa, 2018):

$$\text{‘Pro-EU'}_{nkw} = \gamma\text{‘Post-attack'}_{nkw} + \delta\mathbf{Z}_{nkw} + \lambda_{kw} + u_{nkw} \tag{2}$$

where ‘Pro-EU'$_{nkw}$ captures the response to the above question for individual n, living in region k, interviewed in survey wave w; ‘Post-attack'$_{nkw}$ is a binary indicator that takes value 1 if the individual was interviewed after the day of the attack, and 0 otherwise;[18] $\mathbf{Z}_{nkw}$ is a vector that includes the following individual-level control variables: gender, age, age squared, level of education (low, medium, high) and the political party for which the interviewee voted in the 2015 general election; λ_{kw} represents region-by-wave fixed effects; and, u_{nkw} is an error term.[19] Our parameter of interest, γ, measures the effect of terrorism on EU attitudes, with a positive value indicating that exposure to terrorism sways the population towards a more pro-EU sentiment.

A possible threat to our identification strategy is that individuals with specific characteristics may respond to the survey at different points in time, and these characteristics may be predictive of the outcome. In Section C.3. of the Appendix, we show that there is a strong balance in observed characteristics (included in vector $\mathbf{Z}_{nkw}$) across treatment and control units. To further ensure that our results are not affected by such differences, we report estimates both before and after augmenting the specification with vector $\mathbf{Z}_{nkw}$.[20] Note that the inclusion of region-by-wave fixed effects restricts the pre- and post-attack comparisons to individuals interviewed in the same wave and living in the same region, which can also remove any biases arising from systematic differences in how the different waves were fielded (Balcells and Torrats-Espinosa, 2018). To check the sensitivity of our estimates to the regions considered, we start with the least restrictive specification where regions are captured by GORs and then re-estimate the model using counties[21] and districts as our regional units.

[18] In all three cases, the attack appeared in national newspapers the following day. Dropping individuals who were interviewed on the same day of the attacks leaves our results unchanged.

[19] Section C.1 in the Appendix provides an overview of the variables used in the analysis.

[20] In Section C.3 of the Appendix, we also show that our results persist when we rely on coarsened exact matching to pre-process the data and produce covariate balance between the treatment and control groups.

[21] England, Scotland and Wales are divided into 40 counties (NUTS2 regions).

5.2 Results

Table 4 presents the OLS estimation results of Eq. (2). Column (1) refers to a simple specification that regresses our treatment variable on the outcome variable, whereas columns (2) and (3) progressively add GOR-by-wave fixed effects and the variables in vector $\mathbf{Z}_{nkw}$. The estimates obtained show that citizens take a more positive stance towards the EU after terrorist attacks: the coefficient on 'Post-attack' is positive and highly statistically significant across the three specifications. In columns (4)-(7), we run the same regression set-up as in columns (2)-(3), but we now control for fixed effects at finer administrative levels: counties and districts. The results are little affected by this exercise, both in terms of magnitude and statistical significance. In particular, the estimated coefficient of the treatment variable in columns (2)-(7) suggests that exposure to a new terrorist attack strengthens the pro-EU sentiment by about 0.1 units (1 percentage point on the 0-10 scale).[22] As discussed in the previous sections, geographic proximity to a terrorist attack is expected to amplify the perception of threat and the personal sense of vulnerability, leading to stronger post-attack reactions. Columns (8)-(10) of Table 4 provide evidence in line with this argument. When we restrict the sample to include individuals living in the counties of the three terrorist attacks, the treatment effect becomes nearly four times as large, even though it is now less precisely estimated due to the smaller sample.[23] This finding also adds further support to the use of 'distance from terrorism' as our key explanatory variable in Section 4.

Robustness

In the Appendix, we present additional analyses and robustness checks. In Section C.4, we re-estimate Eq. (2) separately for each attack/wave. In all cases, we find that individuals place themselves closer to the idea of Britain uniting fully with the EU after they are exposed to an attack. However, the results are stronger and statistically more robust for the Manchester Arena bombing

[22]The results are robust to using ordered probit (OP) estimation rather than OLS.

[23]The stronger treatment effect for attacked counties, compared to non-attacked counties, is broadly confirmed when we carry out a test of the hypothesis that estimates on 'Post attack' for the two samples are statistically the same (see Table 4).

which was a highly shocking and sensational event with a large number of casualties. In Sections C.5, C.6 and C.7, we check the sensitivity of our results to using alternative clustering of errors, to accounting for the baseline level of our outcome variable based on a difference-in-differences design, and to using a short-range (3-day) time window. In all cases, our results do not change the inferences from earlier findings. In Section C.8, we perform two placebo tests: one based on an unrelated outcome variable and one based on unrelated time trends. As expected, both tests return (economically and statistically) insignificant coefficients. In Section C.9, we explore the treatment effect on citizens' beliefs about the single most important issue facing the country. The analysis reveals that, after an attack, individuals are far more likely to perceive terrorism as the top national problem as opposed to other popular issues, such as economy and immigration. Finally, in Section C.10, we aggregate the individual-level data to the district level and interact the treatment variable with the distance from terrorist attacks. The corresponding estimates confirm that post-attack reactions are a positive function of geographic proximity to terrorism. Taken together, the alternative estimation strategies and robustness checks presented in Appendix C lend strong credibility to our causal claims.

Risk of terrorism outside the EU

Our results so far demonstrate that exposure to a new terrorist attack increases the positive attitudes towards the EU. One of the arguments put forward in this paper is that, in the aftermath of terrorist attacks, citizens reconsider the risks involved in leaving the EU, particularly in the security domain. To test this argument in a more direct way, we run a final round of analyses and replace the dependent variable with citizens' responses to the following BES question: *"Do you think the risk of terrorism would be higher, lower or about the same if the UK leaves the European Union?"*. The limitation of this question is that it cannot be used for the Manchester Arena bombing (wave 12), as it was included in waves 8 and 13 only. We code the responses *"Higher"* and *"Much higher"* with 1 – and all the other responses with 0 – and estimate a linear probability model using the same regression set-up as in Table 4. We find that, after a terrorist attack, individuals are 1.5 percentage points more likely to report that the risk of terrorism will be higher if the country leaves the EU, and, once again, the results become stronger when we focus on individuals living in the counties of the two terrorist attacks (see Table 5). All in all, our findings confirm that citizens believe that a more effective response to terrorism is at the EU rather than the national level.

6 Conclusions

The UK has long struggled against terrorism and political violence within its borders, which has made counter-terrorism efforts a key priority for policymakers and a main concern for the public. By combining evidence from district- and ward-level data with a wealth of evidence stemming from individual, survey-based data, this paper provides a comprehensive study of the effect of terrorism on voting in the Brexit referendum. Our results suggest that higher exposure to terrorism (as captured by proximity to terrorist attacks) is associated with increased support for Remain. Our results also suggest that that this effect is likely driven by an increase in voters' perception of the benefits of the EU membership and the risks to security and safety posed by the UK's departure from the EU. To assess and substantiate causal inference, we employ alternative estimation strategies and conduct numerous robustness and sensitivity checks, and our results carry over.

Our analysis serves to inform the current ongoing policy debate on the factors that affected the Brexit vote, on public opinion in favor of European unification, and on the short and long-term behavioral and attitudinal consequences of terrorism. While terrorism raises the saliency of security issues and affects overall individual attitudes towards the EU (as documented in this paper), security considerations were perhaps not given sufficient space in the debate leading to the referendum. As Brexit could potentially affect the UK's existing cooperation with law enforcement and intelligence partners by, for instance, limiting the access to data and process systems – such as the European Arrest Warrants and the European Criminal Records Information System – potential risks to counter-terrorism efforts should be taken into account in post-Brexit negotiations.

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Table 1: Terrorism and the Remain vote

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance	-0.022**	-0.024*	-0.027**	-0.023**	-0.022**	-0.026**	-0.030**
	(0.045)	(0.051)	(0.011)	(0.036)	(0.045)	(0.025)	(0.011)
UKIP support		-1.997***					-1.485***
		(0.000)					(0.000)
Austerity shock			-3.770***				-3.627***
			(0.000)				(0.000)
Pensioner share growth				0.472			-0.642
				(0.414)			(0.311)
Population					0.717		0.653*
					(0.138)		(0.056)
Twitter usage (75th percentile)						2.574***	2.248***
						(0.007)	(0.009)
Vector $\mathbf{X}_i$	✓	✓	✓	✓	✓	✓	✓
Attack cluster FEs	✓	✓	✓	✓	✓	✓	✓
R-squared	0.751	0.769	0.787	0.752	0.754	0.759	0.806
Observations	337	335	336	337	337	337	335

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; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 2: Terrorism and turnout

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance	-0.004	-0.004	-0.003	-0.006	-0.004	-0.004	-0.004
	(0.317)	(0.256)	(0.454)	(0.104)	(0.320)	(0.379)	(0.280)
UKIP support		-0.123					0.120
		(0.310)					(0.228)
Austerity shock			-2.022***				-1.812***
			(0.000)				(0.000)
Pensioner share growth				1.176***			0.553*
				(0.000)			(0.053)
Population					-0.385		-0.326
					(0.117)		(0.107)
Twitter usage (75th percentile)						-0.237	-0.061
						(0.532)	(0.851)
Vector $\mathbf{X}_i$	✓	✓	✓	✓	✓	✓	✓
Attack cluster FEs	✓	✓	✓	✓	✓	✓	✓
R-squared	0.835	0.840	0.879	0.856	0.839	0.836	0.892
Observations	337	335	336	337	337	337	335

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

Table 3: Terrorism, the Remain vote and turnout:
IV estimates

	Remain		Turnout	
	(1)	(2)	(3)	(4)
Distance	-0.031**	-0.032***	-0.011**	-0.009***
	(0.012)	(0.000)	(0.021)	(0.001)
UKIP support		-1.485***		0.121
		(0.000)		(0.172)
Austerity shock		-3.628***		-1.814***
		(0.000)		(0.000)
Pensioner share growth		-0.636		0.570**
		(0.259)		(0.024)
Population		0.659**		-0.311*
		(0.029)		(0.068)
Twitter usage (75th percentile)		2.269***		-0.009
		(0.002)		(0.975)
First stage				
Distance (1970-1979)	0.925***	0.913***	0.925***	0.913***
	(0.000)	(0.000)	(0.000)	(0.000)
Vector $\mathbf{X}_i$	✓	✓	✓	✓
Attack cluster FEs	✓	✓	✓	✓
Excluded F-stat	152.207	121.945	152.207	121.945
Observations	337	335	337	335

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

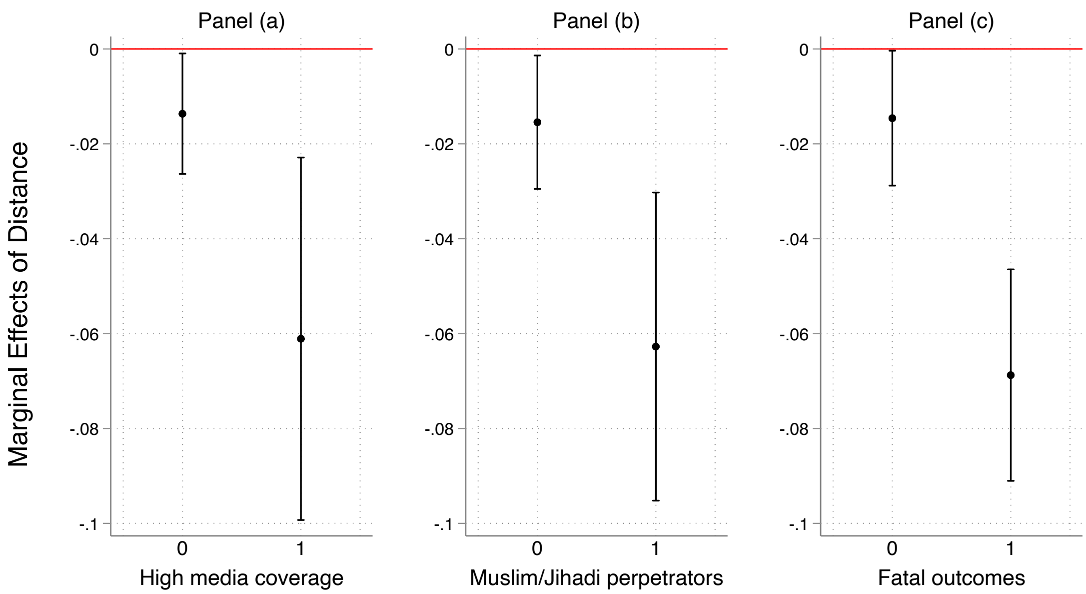

Figure 1: Heterogeneous effects

Notes: Marginal effects of 'Distance' at 0 and 1 values of the three conditioning binary variables. The dependent variable in all three panels is 'Remain'. The estimates are calculated based on the specifications of columns (1), (3) and (5) in Table A.9 of the Appendix. All other covariates are held constant at their means. Solid vertical lines signify 95% confidence intervals. Red horizontal line marks marginal effect of 0.

Table 4: Terrorism and pro-EU sentiment: individual-level analysis

	All respondents							Within attacked counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post-attack	0.202***	0.130***	0.093***	0.136***	0.093***	0.126***	0.083**	0.453**	0.373*	0.313*
	(0.000)	(0.000)	(0.006)	(0.000)	(0.006)	(0.001)	(0.015)	(0.033)	(0.082)	(0.074)
GOR-by-wave FEs		✓	✓							
County-by-wave FEs				✓	✓					
District-by-wave FEs						✓	✓		✓	✓
Vector $\mathbf{Z}_{nkw}$			✓		✓		✓			✓
R-squared	0.001	0.035	0.320	0.044	0.322	0.073	0.336	0.003	0.059	0.331
Observations	72,828	72,828	62,529	72,828	62,529	72,828	62,529	1,920	1,920	1,650
Diff-test								0.054	0.109	0.080

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 5: Perceptions of terrorism outside the EU: individual-level analysis

	All respondents							Within attacked counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post-attack	0.015***	0.015***	0.015**	0.015***	0.015**	0.015**	0.015**	0.059**	0.061**	0.037
	(0.008)	(0.008)	(0.013)	(0.008)	(0.013)	(0.013)	(0.017)	(0.043)	(0.031)	(0.251)
GOR-by-wave FEs		✓	✓							
County-by-wave FEs				✓	✓					
LAD-by-wave FEs						✓	✓		✓	✓
Vector $\mathbf{Z}_{nkw}$			✓		✓		✓			✓
R-squared	0.000	0.004	0.051	0.006	0.052	0.020	0.066	0.002	0.027	0.100
Observations	52,338	52,338	44,537	52,338	44,537	52,338	44,537	1,278	1,278	1,083
Diff-test								0.040	0.026	0.226

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.

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

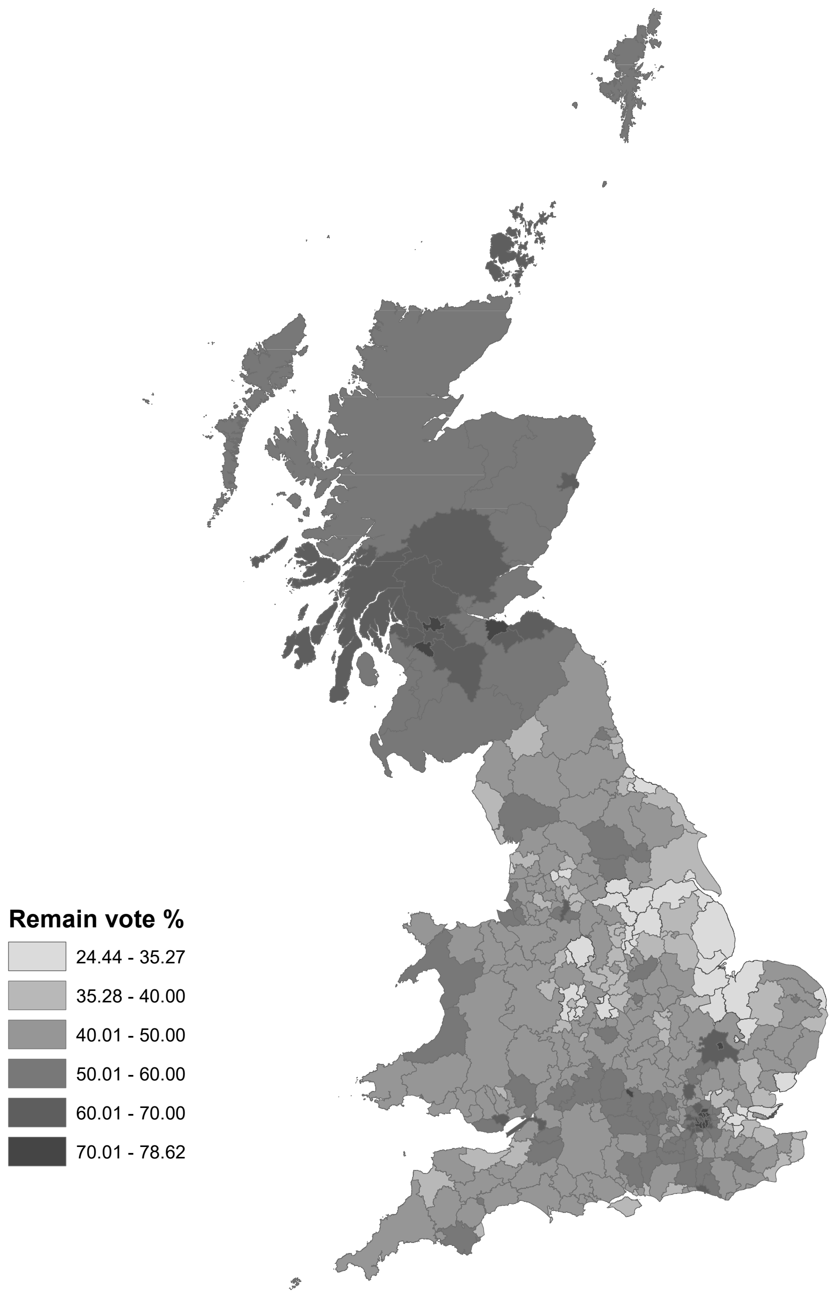

Figure A1: Remain vote share across districts (LADs)

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.

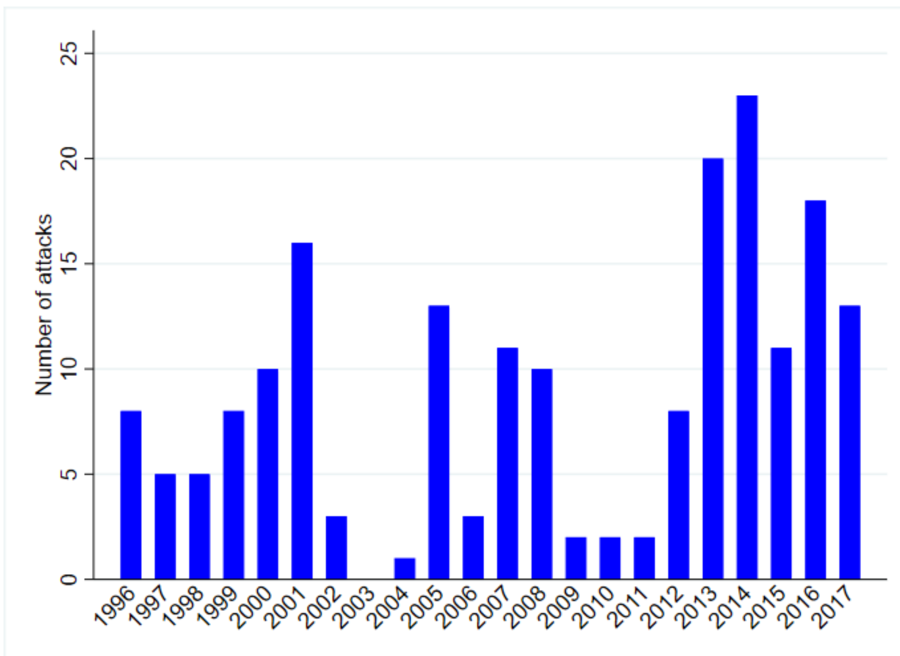

Figure A2: Frequency of terrorist attacks in England, Scotland and Wales from 1996 to 2017

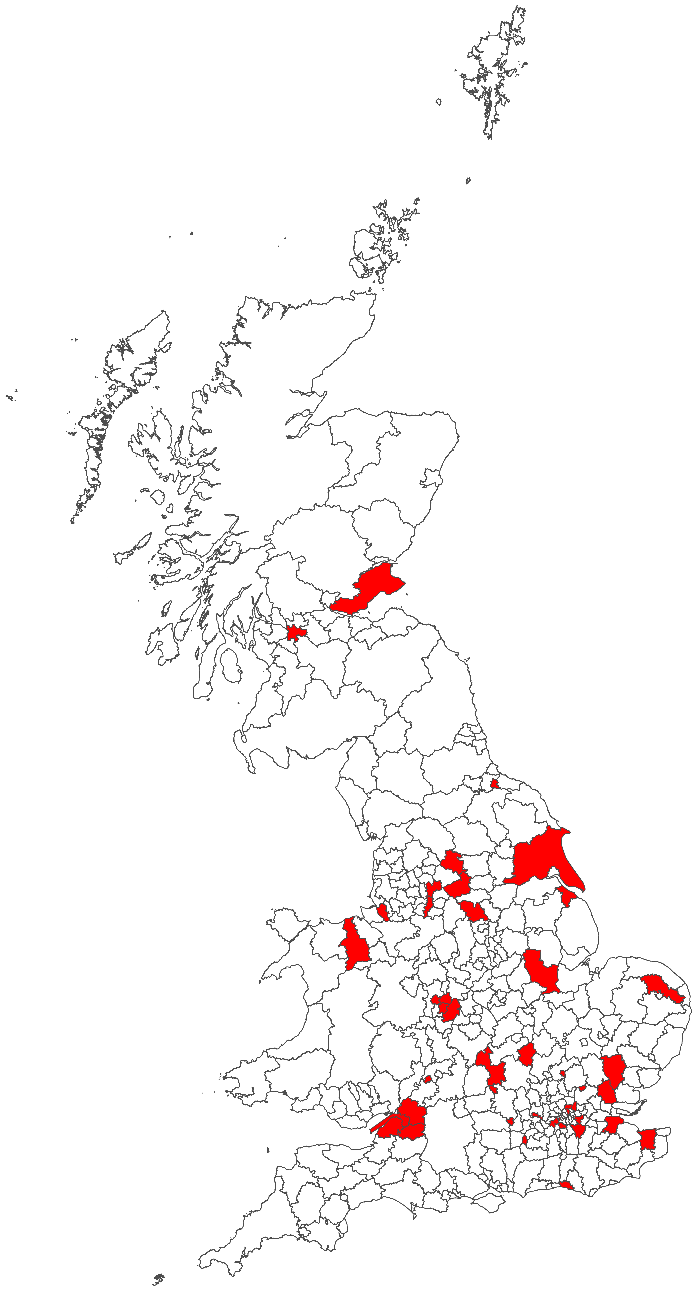

Figure A3: Terrorist-hit districts (LADs)
Notes: Red shades correspond to districts that were hit by terrorist attacks from January 2013 to the referendum date.

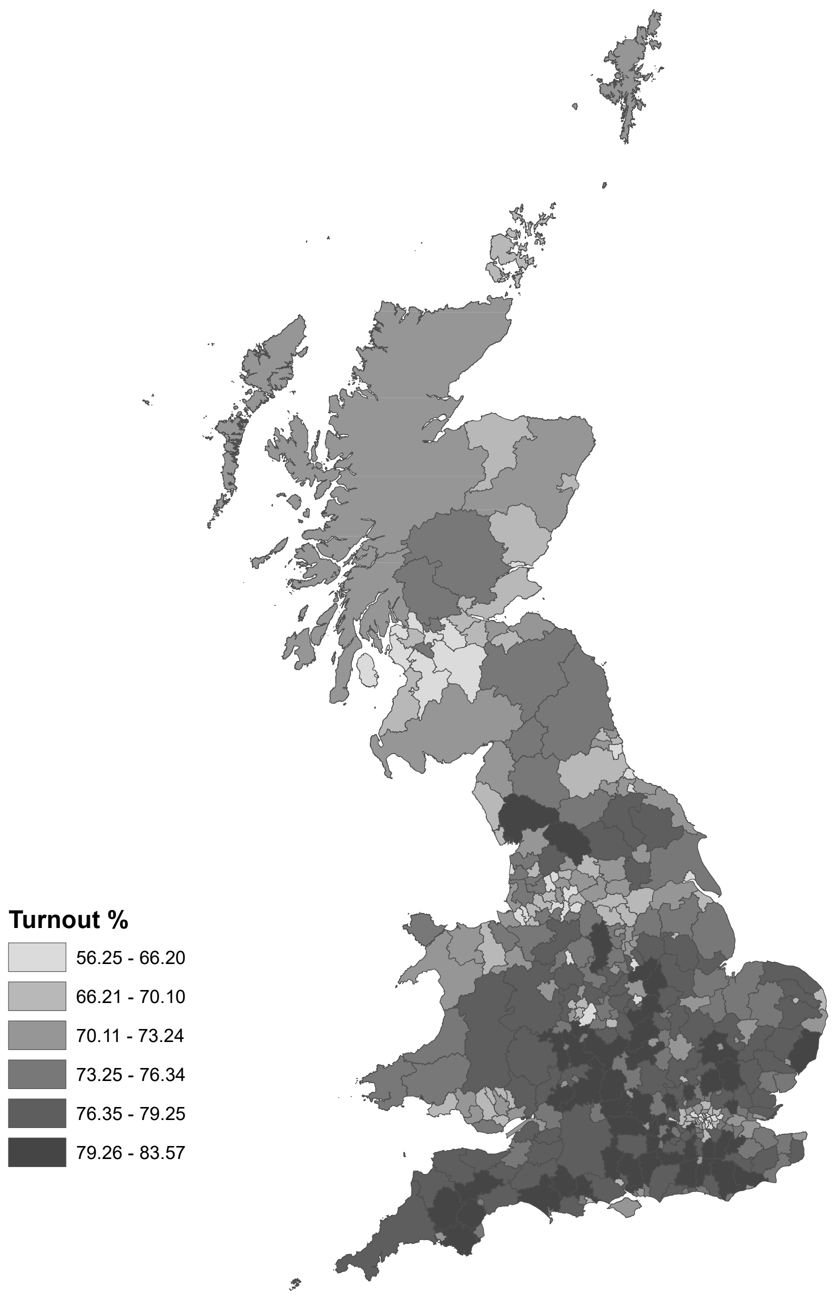

Figure A4: Turnout rate across districts (LADs)

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.

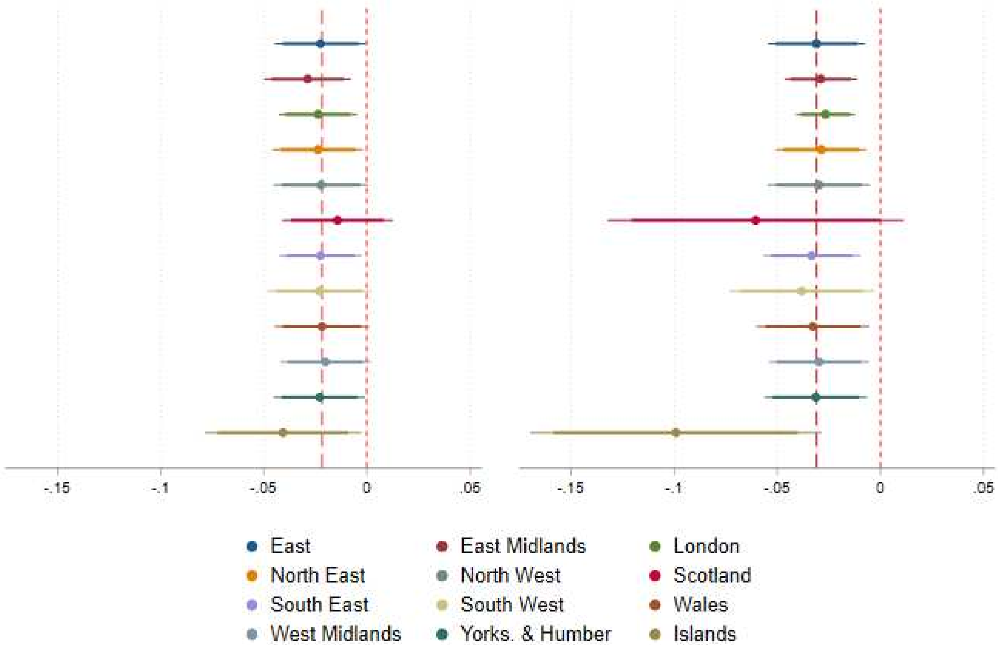

Figure A5: GOR and island exclusion

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

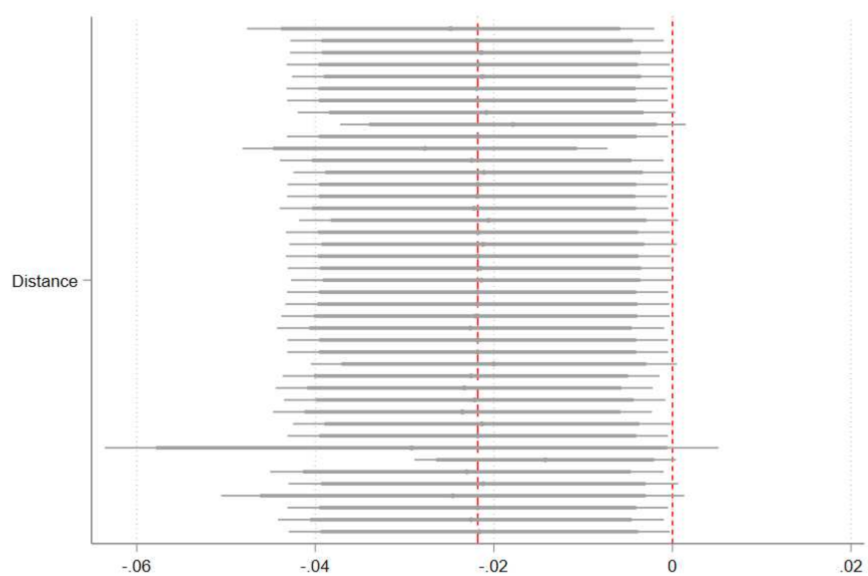

Figure A6: Attack cluster exclusion

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; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

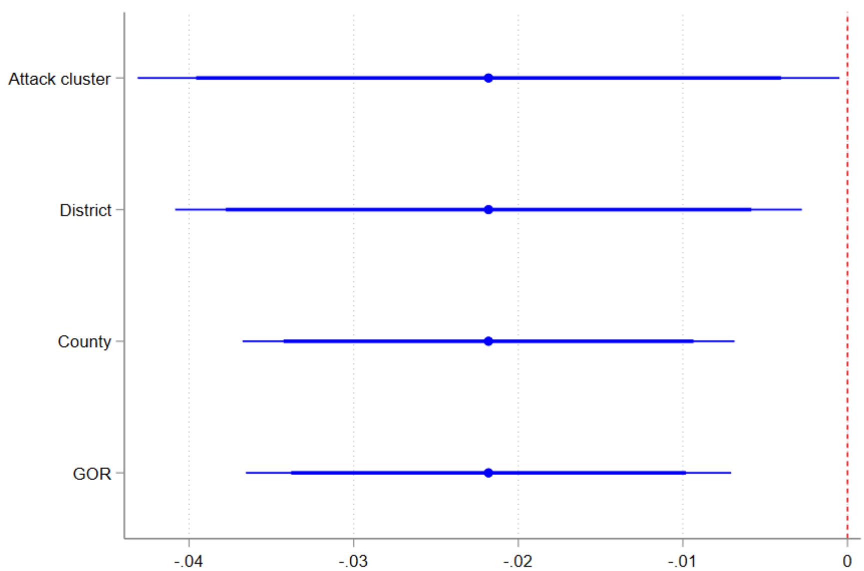

Figure A7: Alternative clustering of errors
Notes: Fat and thin whiskers indicate confidence intervals at the 90% and 95% levels, respectively.

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) (1)	Invalid votes (2016) (2)	Economy worse? (3)	Personal finances worse? (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. 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

	(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 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; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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

Kashmira Gander

Mark Steel

Sean O'Grady

Ian Herbert

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

Saffie, 8, whose mum is fighting for her life

As suicide bomber who killed 22 in Manchester is revealed to be a British-born jihadi, PM orders . . .

SOLDIERS ON THE STREETS

(b) Attack #2

Amazing art and design
The summer's best shows

Kamila Shamsie
Pakistan's cricketing triumph

Glastonbury fashion
Wellies and wet wipes

theguardian

Fresh terror in London as van drives into crowd at mosque

UK yields to EU on first day of Brexit negotiations

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

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.

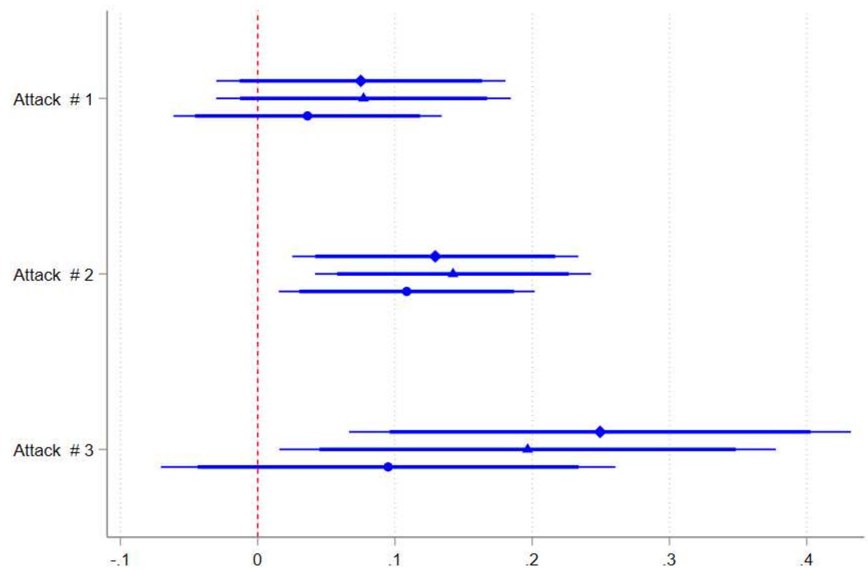

Figure C2: Terrorism and pro-EU sentiment: single attacks

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.

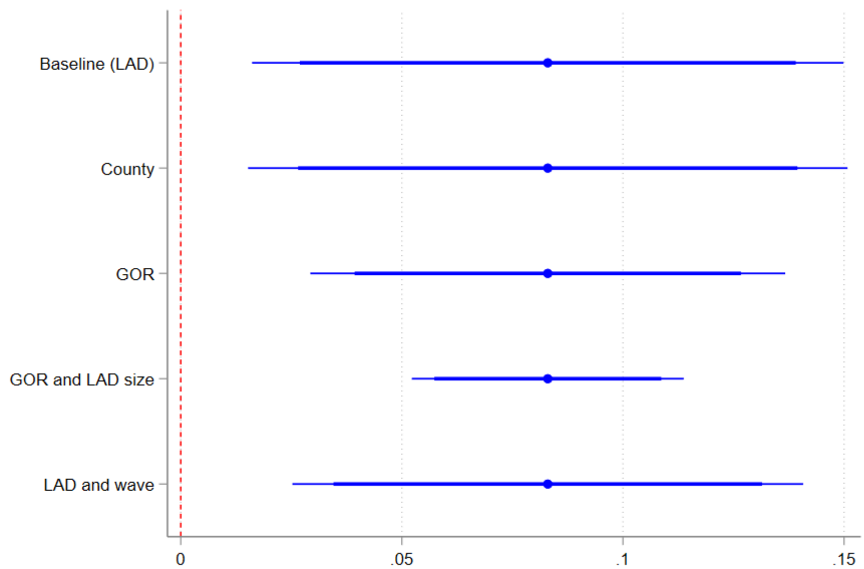

Figure C3: Alternative clustering of errors

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]

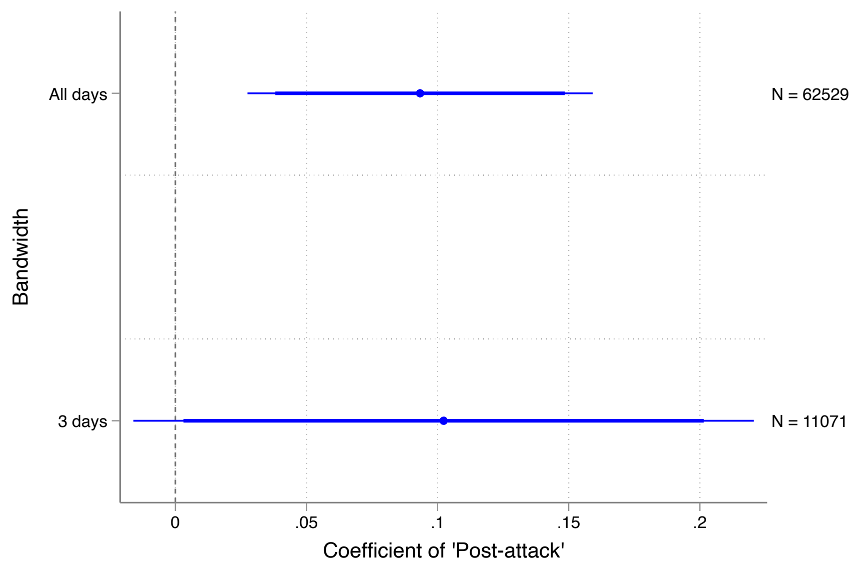

Figure C4: 3-day time window

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.

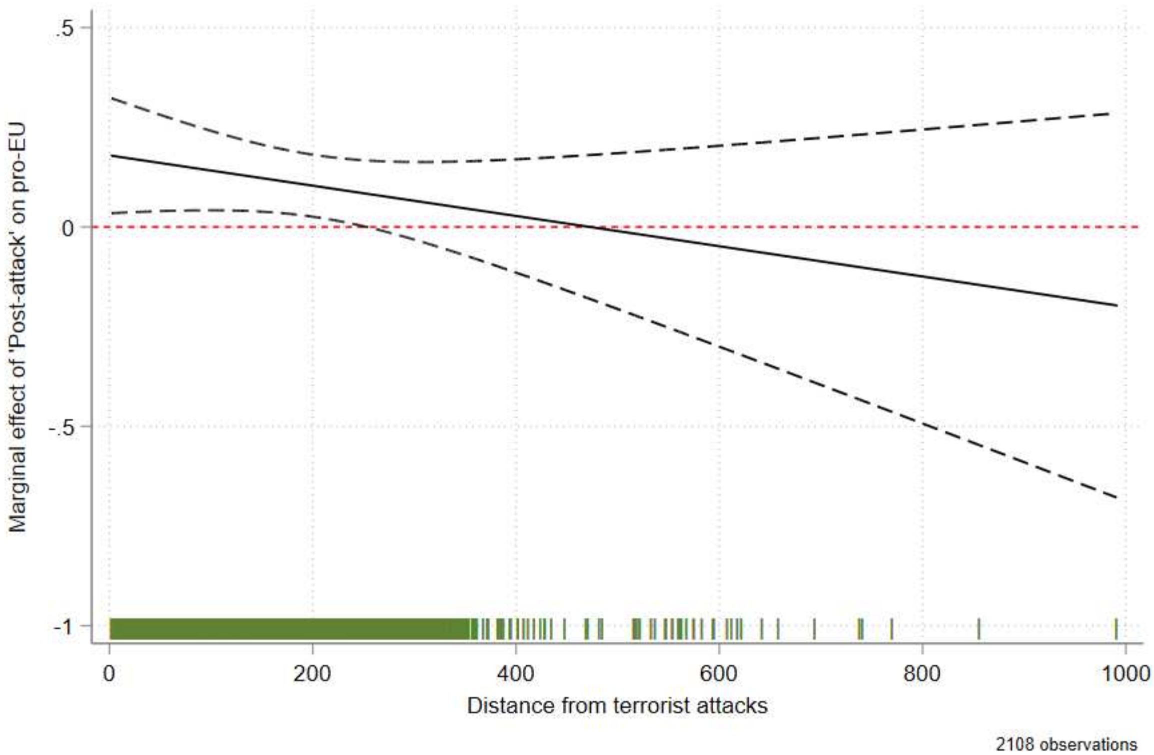

Figure C5: Marginal effects of 'Post-attack'

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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