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# Jihadi Attacks, Media and Local Hate Crime

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## Abstract
Empirical connections between local anti-Muslim hate crimes and international jihadi terror attacks are studied. Based upon rich administrative data from Greater Manchester Police, event studies of ten terror attacks reveal an immediate big spike up in Islamophobic hate crimes and incidents when an attack occurs. In subsequent days, hate crime is amplified by real-time media. It subsequently attenuates, but hate crime incidence cumulates to higher levels than prior to the series of attacks. The overall conclusion is that, even when they reside in places far away from where jihadi terror attacks take place, local Muslim populations face a media magnified likelihood of hate crime victimization following international terror attacks. This matters for community cohesion in places affected by discriminatory hate crime and, from both a policy and research perspective, means that the process of media magnification of hate crime needs to be better understood.

Key words: Islamophobic hate crime, jihadi terror attacks, media
JEL Codes: K42

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## 1. Introduction

Against a backdrop of a rise of populist politics in the Western world, a wave of refugee migration (especially from Muslim countries), and drops in real living standards following the global financial crisis of 2007/8, the number of jihadi terrorist attacks taking place around the world accelerated. Various commentators have argued these have conspired to fuel more Islamophobia, that anti-Muslim sentiments have risen in Western democracies, and that this has had a divisive impact on minority communities.[1]

Whether terror attacks themselves result in a higher occurrence of hate crimes against certain groups in society has been a research focus in a small, but growing, body of social science research.[2] In economics, discriminatory hate crimes impose significant individual costs on victims, and a wider social cost on communities by causing significant problems that cumulate over time.[3] The research by Gould and Klor (2016), for example, presents strong and credible evidence that jihadi terror attacks induced a significant slowdown in assimilation of Muslim immigrants in US states more affected by local hate crimes.[4]

Empirical evidence demonstrates that terror attacks in specific places do induce opportunistic hate crimes. The most well-known and studied terrorist attacks – 9/11 in the US and 7/7 in London – featured significant spikes up in hate crimes committed against Muslims in various places, some of which are geographically remote from the location of the jihadi terrorist attacks (Swahn, Mahendra, and Paulozzi, 2003; Poynting and Noble, 2004; Sheridan and Gillett, 2005; Amer and Bagasra, 2013; Hanes and Machin, 2014; King, DeMarco and VandenBerg, 2016).

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[1] See, inter alia, Bansak, Hainmueller and Hangartner (2016).
[2] See, for example, the collection of papers in a 2014 special issue of the Journal of Contemporary Criminal Justice on "Crime and Prejudice: Innovations in the Study of Hate Crime and Extremist Violence".
[3] Huntington developed the hypothesis in The Clash of Civilizations that the fundamental source of conflict in the new world will not be primarily ideological or economic, but between cultures, and that Islamic extremism and its consequences would become the biggest threat to world peace.
[4] For detailed study of who engages in terrorist activity see Krueger (2007) and for examples of empirical studies on the economic effects of terrorism see Abadie and Gardeazabal (2003), Frey, Luechinger and Stutzer (2007) or Gould and Klor (2010).

Subsequent studies on Islamophobia have studied hate crime incidence from both a general societal and a minority group perspective. Some of these document increases in Islamophobic violence against either Muslims or those that appear to be Muslim (Perry, 2014; Abu-Raiya et al., 2011; Abu-Ras and Suarez, 2009). The role of the media as a transmission mechanism in facilitating reaction in distant places has also been studied (as, for example, discussed in the arguments made in Gentzkow and Shapiro, 2004).[5] The main argument is that attitudes and behaviour (including criminality) towards particular groups like Muslims have scope to be altered by actual attacks and that they can be triggered or magnified by media coverage of attacks. Thus, 'attitudinal shocks' may cause individuals (maybe with a prior inclination being tipped over a threshold by the media activity) to become perpetrators of hate crime.

This paper offers new, large-scale quantitative evidence on Islamophobic hate crime and incident occurrence following international jihadi terror attacks. It uses rich, high frequency administrative data from Greater Manchester Police. A relatively long time window offers an opportunity to carefully appraise how a sequence of jihadi attacks occurring in other parts of the world have scope to both impact upon local hate crime, and to exert a longer run impact. The unique nature of the data, and the unpredictability of terror attacks, provide a quasi-experimental setting allowing reliable conclusions to be drawn on the temporal impact of jihadi terror attacks on local Islamophobic hate crimes and incidents, the direction of causality between media and hate crime, and on the characteristics of hate crime perpetrators and their victims.

[5] For a wider ranging discussion of research on the economic and social impacts of the media, see DellaVigna and La Ferrera (2016). A very interesting example of the impact of media – in this case radio – on racial hate crime can be found in DellaVigna et al. (2014), describing the case of cross-border nationalistic Serbian radio triggers ethnic hatred towards Serbs in Croatia. As a result, the vote for extreme nationalist parties was higher in Croatian villages with Serbian radio reception. More generally, DellaVigna and Kaplan (2007) describe the impact of Fox news being available in American certain cable markets on voter turnout and Republican vote share.

To preview the main findings, immediately following ten international terror attacks the number of Islamophobic hate crimes and incidents in Manchester rapidly surge. There is an instant spike up, which then attenuates in subsequent weeks but with hate crime incidence cumulating to higher levels than prior to the series of attacks. Anti-Muslim hate crimes and incidents are more likely to be committed in socially deprived areas with a high Muslim population, and are spatially highly concentrated. The demographic profile of perpetrators of hate crime is specific, with offenders being comparatively older and more likely to travel from nearby communities with different demographic structures to predominantly Muslim neighbourhoods to commit hate crimes.

The role of the media is explored. Daily data reveals real-time media to be a causal mechanism underpinning the surge in local hate crimes and incidents that occur following an attack. A peak in hate crime sometimes occurs on the second and third day following the attack, which provides support that Islamophobia is not only an immediate response to the attack, but is additionally incited by the information on perpetrators and victims presented by the media over the days following the attack. Therefore, the paper concludes that Muslim populations face a media magnified likelihood of hate crime victimization even when they reside in places far away from where jihadi terror attacks take place. This matters for community cohesion in places affected by discriminatory hate crime and, from both a policy and research perspective, means that the process of media magnification of hate crime needs to be better understood.

The rest of the paper is structured as follows. Section 2 describes the data and context. Section 3 outlines a research design based on the notion that jihadi terror attacks can provide natural or quasi-experimental variations that have scope to alter attitudinal perceptions of minority groups and thereby lead to hate crime. It also offers descriptive statistics and data visualisation on hate crime incidence before and after terror attacks. Section 4 reports the main statistical results, and further assesses and probes the robustness of the key findings. Section 5 considers the potential role of the media, offering several pieces of evidence that show the direction of causality runs from media to local hate crime and not the other way around. Section 6 presents contextual findings on hate crime perpetrators and the nature of the offences they commit. Section 7 concludes by discussing the implications of the different pieces assembled throughout the paper.

## 2. Data and Study Context

### *Data*

The data are mostly administrative records, made available by the Greater Manchester Police (GMP), from 1st April 2008 to 31st July 2018. The main source of data is the GMP's Command and Control dataset, to which we were granted full and complete access. This dataset contains the population of recorded incidents and crimes (over ten million of them), including the precise time of the event and its location recorded as latitude and longitude.

The GMP proprietary data are complemented with publicly available data from the 2011 Census for England and Wales that provides a detailed snapshot of the population and its characteristics in March 2011. These data are aggregated to lower layer super output areas (LSOA), a spatial level that encompass a median of around 650 households, or 1500 people. In the Greater Manchester area, there are 1671 LSOAs. This very detailed spatial granularity is exploited in the different pieces of empirical evidence offered in the paper.

### *Hate crimes and incidents*

In common with other police forces in England and Wales, GMP records and categorises hate incidents and hate crimes according to national standards. Since recording was first introduced in 1994, a number of refinements have been made to the definitions and classifications in order to recognise changes in society – the most recent refinement was the recognition of 'hate' motivated by an individual's alternative sub-culture. Antisemitic and

Islamophobic hate incidents and crimes have therefore been recorded since April 2007. This defines the starting point of the analysis of this paper, namely April 2008.

GMP's policy and procedure is based on the College of Policing's Hate Crime Operational Guidance. The force's approach is to make positive interventions and take firm action against offenders whenever there is sufficient evidence and, where appropriate, explore restorative justice opportunities, maintaining at all times a focus on the victim. Regular officer training and information campaigns explain what is meant by a hate incident or a hate crime and GMP encourages the public and other organisations to report their occurrence.

Specifically, GMP defines hate incidents as those perceived by the victim or any other person to be motivated by hostility or prejudice based on a person's alternative sub-culture identity - disability, race, religion, sexual orientation - or perceived alternative sub-culture identity. A hate crime is any criminal offence of the aforementioned definition. Islamophobic hate crimes are one of the various hate crimes recorded by the police. GMP defines Islamophobia as "the fear and/or hatred of Islam, Muslims or Islamic culture. It is also a phrase that is used to describe any remark, insult or act, the purpose or effect of which is to violate a Muslim person's dignity or create an intimidating, hostile, degrading, humiliating or offensive environment. This definition can be applied to individuals and to the Muslim community as a whole." An Islamophobic incident follows the same logic and definition as Islamophobic hate crimes. In general, these records are identified using an "Islamophobic marker". This flag will need to be set if the crime or incident was marked as "Hate". The other hate crime subgroups used in the empirical analysis refer to Disability[6], Antisemitism[7] and Sexual orientation[8].

*Jihadi Terror Attacks*

The analysis considers ten jihadi terrorist attacks that took place between 2008 and 2018 that satisfied the following choice criteria: occurring in the UK; occurring in Western Europe with five or more fatalities; and the attack in Tunisia (in 2015) which was an attack on a resort with a significant number of UK victims. The ten attacks are: the Lee Rigby murder in London (May 2013); the Charlie Hebdo attack in Paris (January 2015); the Sousse attack in Tunisia (June 2015); the Paris attack (November 2015); the Brussels attack (March 2016); the Nice attack (July 2016); the Berlin attack (December 2016); the London Westminster attack (March 2017); the Manchester Ariana Grande concert attack (May 2017); and the London Bridge attack (June 2017).[9]

## 3. Research Design and Initial Descriptive Analysis

*Modelling Approach*

A difference-in-differences (D-i-D) empirical research design is set up to study how international jihadi attacks affect anti-Muslim hate crime in Greater Manchester. Data is available on hate crimes committed against four different groups i (i = Islamophobic, Disabled, Antisemitic, Sexual orientation). The initial baseline specification is the following D-i-D model

[6] Disability hate crimes are recorded in accordance with the Equality Act's definition. The Equality Act 2010 covers a wide variety of disabilities and can include the following: sensory impairment, mental health, learning difficulties, mobility, hidden (for example, muscular dystrophy and HIV) and other (for example, severe disfigurement). Hence, if anyone perceives an incident to be motivated by hostility or prejudice due to a person's disability or perceived disability, GMP will record it as such.

[7] Antisemitism refers to any remark, insult or act, the purpose or effect of which is to violate a Jewish person's dignity or create an intimidating, hostile, degrading, humiliating or offensive environment. The definition can be applied to individuals and to the Jewish community as a whole. An antisemitic incident is any incident which is perceived to be antisemitic by the victim, or any other person.

[8] Sexual orientation is the phrase that is used to describe an individual's physical and/or emotional attraction to others and, therefore, includes people who identify themselves as gay, lesbian, bisexual or heterosexual. A hate incident marked as such is any incident that is perceived to be motivated by the sexual orientation of the victim.

[9] As a robustness analysis in Section 5, we also use the number of articles on jihadi terrorist attacks in UK National newspapers to allow for the effect of other international jihadi attacks than the ten we have identified.

where before/after terror attack changes are compared between the Islamophobic group and the other three hate crimes:

$$\text{Log}(\text{Hate}_{it}) = \beta_1[\text{Islamophobic}_i \text{ x } (\text{Terror attack})_t] + \delta_t + \alpha_i + u_{1it} \qquad (1)$$

where $\text{Hate}_{it}$ is the number of hate crimes and incidents committed against group i at time t, $\alpha_i$ is a dummy variable identifier for group i, $(\text{Terror attack})_t$ is a dummy variable indicating that a jihadi attack occurred in period t and $\delta_t$ is a full set of time dummies, which therefore absorb the levels effect of $(\text{Terror attack})_t$. Finally, $u_{1it}$ is a random error term.

In (1) $\beta_1$, the estimated coefficient on the interaction term $[\text{Islamophobic}_i \times (\text{Terror attack})_t]$, is the D-i-D estimate of the impact of the international jihadi attacks on Islamophobic hate crime. The estimate of $\beta_1$ can be interpreted as causal if jihadi terrorist attacks outside of Manchester do not occur on weeks when, for unrelated reasons, Muslims in Manchester are particularly likely to be the targets of hate crime (relative to other traditionally vilified groups). In addition, for this to be a legitimate research design, there needs to be no differential pre-trends between the different groups. These are carefully examined in the empirical analysis that follows, by further developing equation (1) in specific directions of interest.

A first way of doing this is to further augment equation (1) with a richer set of time effects. One reason to include these is to flexibly control for the fact that the number of jihadi attacks has been increasing over time. A second reason is due to the highly seasonal nature of crime and a third is the potential diverging trends in the sub-groups of hate crime over the 2008-2017 period. Thus, an equation containing a more flexible set of time effects, allowing there to be differential trends for different hate crime groups, can be specified as:

$$\text{Log}(\text{Hate}_{it}) = \beta_2[\text{Islamophobic}_i \text{ x } (\text{Terror attack})_t] + \delta_t + \alpha_i + [\alpha_i \text{ x } f(t)] + u_{2it} \qquad (2)$$

where f(t) is a general time function. In practice, group x quarter or group x year interactions are included.

To evaluate possible differences in timing patterns, the model can be re-specified to include pre- and post-attack variations in the D-i-D estimate in an event study setting. Inclusion of pre-attack variation is important for whether the parallel pre-trends assumption that is required for the D-i-D estimate to be unbiased holds. Inclusion of post-attack variation permits more to be said about whether any impact is short run or whether it persists beyond the attack incident period. In most of the analysis, the D-i-D specification is generalised into an event study featuring three pre- and post-attack time periods as follows:

$$\text{Log}(\text{Hate}_{it}) = \sum_{t=-3}^{t=3} \beta_{3,t}[\text{Islamophobic}_i] \text{ x } (\text{Terror attack})_t] + \delta_t + \alpha_i + [\alpha_i \text{ x } f(t)] + u_{3it} \qquad (3)$$

The final specification recognises that not all terror attacks speak to the question of whether it is attacks taking place some distance away that potentially affect hate crime in Manchester. In fact, the last attack considered in the paper is an attack in Manchester itself (the Ariana Grande concert attack of May 2017). This was followed relatively soon after (in June 2017) by the London Bridge attack. It is natural to think that there may be different magnitude impacts from these more local attacks. Thus, a yet more general specification allows for separate effect for these more "Recent terror attack" incidents in equation (4) below:

$$\begin{aligned} \text{Log}(\text{Hate}_{it}) = &\sum_{t=-3}^{t=3} \beta_{41,t}[\text{Islamophobic}_i] \text{ x } (\text{Terror attack})_t] + \\ &\sum_{t=-3}^{t=3} \beta_{42,k}[\text{Islamophobic}_i] \text{ x } (\text{Recent terror attack})_t] + \\ &\delta_t + \alpha_i + [\alpha_i \text{ x } f(t)] + u_{3it} \end{aligned} \qquad (4)$$

*Initial Descriptive Analysis*

Summary statistics are presented in Table 1. The sample covers 538 time series data points per hate crime group, for each week in the eleven and a half years between April 2008 and August 2018 inclusive. Ten terror attacks occur in 1.8 percent of the weeks in the sample.

The upper part of the Table shows that over all weeks there are around 5 Islamophobic recorded hate crimes per week, and around 4 Disabled, 3 Antisemitic and 11 Sexual orientation hate crimes respectively.

The lower part of the Table considers differences between the ten terror attack weeks and the 528 non-terror attack weeks. There is a big divergence in the case of the Islamophobic hate crimes that feature an average of 19 across the ten terror weeks as compared to 4 in the non-terror weeks (the gap of 14.99 is strongly significant in statistical terms). Thus, by this comparison, they are nearly five times more likely to happen. The Non-Islamophobic hate crimes are also higher, but proportionately much less so at 21 versus 18 crimes respectively (though the gap of 3.17 is not statistically significant). Finally, a raw difference-in-differences is reported in the bottom row of the Table, showing hate crimes to be 12 crimes higher than the comparison group in the before and after comparison (the precise gap of 11.82 hate crimes being strongly significant in statistical terms).

The month by month temporal variation in Islamophobic crimes and incidents in the period of April 2008 to August 2018 is shown in the upper panel of Figure 1. Two stark visual observations are evident. First, there is an upward trend in hate occurrence in the period from 2015 to 2017. The mean of monthly hate crimes and incidents varied around 15 hate crimes and incidents, on average, from 2008 to 2015, while it doubled to on average 30 hate crimes and incidents in the period from 2015 onwards. Second, and this will become much clearer in what follows, the peak monthly frequencies closely correspond to the period following the international jihadi attacks that are studied. The lower panel of Figure 1 plots the weekly variation in Islamophobic crimes and incidents in 2017. The Manchester May 22$^{nd}$ attack and the London Bridge 3$^{rd}$ June attack led to two subsequent spikes, quadrupling the observed Islamophobic hate crimes and incidents in the weeks following the attacks.

Two more patterns seen in these data are worthy of note and further discussion. First, there is a clear pattern of edging up in the occurrence of hate crimes and incidents after each of the ten terror attacks. Second, and at least partially a consequence of this, by 2018 the number of anti-Muslim hate crimes and incidents stands at a considerably higher level than before the attacks occurred. In fact, by 2018 there are around four times more such hate crimes and incidents than there were at the start of the data coverage time period ten years before in 2008.

## 4. Results

In this section, we first show a set of general baseline estimates. These are then subsequently further refined and extended by in turn focusing on specific issues to do with timing and location of attacks.

*Baseline Estimates*

The starting point for the statistical work is the D-i-D model that was introduced in Section 3. Table 2 presents difference-in-differences estimates of the causal impact of the jihadi terror attacks based upon weekly panel data. The specifications in columns (1) to (3) show the baseline terror attack impact in the week of the attacks, and those in columns (4) to (6) show event study estimates that include additional impacts for the three preceding and post-attack weeks. There are three specifications in each case, which differ in how the various fixed effects are entered. Columns (1) and (4) are conventional models where additive fixed effects for the four hate crime groups i and a full set of time fixed effects for the 538 weeks are included. The other specifications allow for time varying group effects by including crime group by year interactions (in (2) and (5)) and crime group by quarter interactions (in (3) and (6)).

The dependent variable is the log of the hate crime count and so the estimates can be read as proportionate effects. In all specifications, there is a positive and statistically significant effect of jihadi terror attacks on Islamophobic hate crimes and incidents. The magnitudes are large. Columns (1) to (3) show a significant spike up in the week of the attack which, dependent on specification, is of the order of 0.75 to 0.99 log points higher relative to the other hate crimes. The event study estimates show that there is not any discernible pre-trend, and that the terror attack week spike up is of similar magnitude (between 0.75 and 0.96 log points). Moreover, the effects persist and, whist they attenuate compared to the attack week, they remain significantly higher than pre-attack levels three weeks after the attacks took place.

Estimates from the column (5) specification are portrayed visually in Figure 2, which very clearly shows there to be no evidence of differential pre-trends in the three weeks before the attack, a very sizable jump up in the week of the attack itself, followed by higher levels post-attack for three weeks, with a decaying of the impact as one moves further in time away from the attack week. Nonetheless, the levels of Islamophobic hate crime remain higher, so that cumulatively Islamophobic hate crime stays at a higher level after the attacks occurred. Considering that the estimates show the average across the ten attacks that occurred, this shows how levels of Islamophobic hate crime are at permanently higher levels in 2018 when the sample studied here ends than they were prior to the ten attacks taking place.

*Recording*

One possible issue with the results shown so far concerns police methods of recording hate crimes and whether there may have been potential changes in recording hate crime incidents and crimes in the aftermath of a terrorist attack. First, after extensive conversations with the Greater Manchester Police staff we can be certain that there were no organizational changes in recording hate crime in our sample period. Neither was there an increased sensitivity about potential Islamophobia in the aftermath of the terrorist attacks about recording (or more detailed inquiry about the nature of offences) nor increased patrolling. As nine out of the ten terrorist attacks occurred outside of Greater Manchester (and six were outside of the United Kingdom) we find this credible.

Second, it is possible to set up empirical tests of this. Table 3 shows estimates that should not be sensitive to possible changes in patrolling or recording on the behalf of the police. It does so by narrowing down the hate crime measures to those that were only incidents and crimes self-reported by the victim, and to 999 calls made to the police. The first two columns of the Table reproduce the columns (2) and (5) specifications from Table 2 (i.e. those additionally include hate crime group by year fixed effects to the baseline model), whilst columns (3) and (4) show analogous estimates for self-reported hate crimes and (5) and (6) do the same for 999 calls made to the police. In broad terms comparing across the relevant specifications in the Table, the results are highly similar, still showing a spike up in the attack week, and persistence for up to three weeks later.

*Heterogeneity Across Attacks*

Using variation in the timing of international jihadi terror attacks to consider variations in hate crime incidence in Manchester relies on the notion that the timing of the attacks is orthogonal to policing in Greater Manchester. Whilst this seems eminently reasonable for attacks taking place in other countries, one might question the credibility of the assumption for the attacks in the sample that took place in the UK, and especially the one attack in Manchester itself. Thus, it could be the case that the London Westminster attack in March 2017, the Manchester 22$^{nd}$ May 2017 attack, and the London Bridge attack on 3$^{rd}$ June 2017 could have affected local policing in Manchester in the weeks following these attacks.

This is studied in two ways in results shown in Table 4. First, as shown in columns (1) and (2), the main specifications were run only on data covering weeks up to the end of 2016, therefore excluding the last three attacks. This way it is possible to avoid the results being driven solely by the 'local' attacks. Second, as shown in columns (3) and (4), the full sample was used, but specifications allowed there to be a separate effect for the three post-2016 attacks.

For the estimates ending in 2016, there is again evidence of a positive and significant spike up for the week of the attack (see column (1)). However, closer exploration does reveal that the magnitude is a little smaller than for the full sample (at 0.69 log points compared to the earlier estimate of 0.84 log points). Moreover, as the column (2) specification shows, there is still persistence in the estimated impacts, but it does not last quite as long.

For the estimates that allow for heterogeneity by groups of attacks, there is indeed evidence of a bigger spike up in the attack week for the recent attacks. As column (3) shows, the jump is 0.62 log points for the earlier attacks and a far higher 1.72 log points for the more recent attacks. Column (4) also shows that the persistently higher levels of Islamophobic hate crime after the event is a stronger feature of the more recent attacks.[10] Hence, the more recent attacks were connected to bigger and more persistent hate crime increases. This in itself is an important insight, with the worsening of hate crime and incident victimization of the Muslim population as a reaction to the recent jihadi terror attacks. It is also important for the discussion of possible media magnifications, and especially their timing and causal relation with hate crime, that is considered in detail in the next section of the paper.

## 5. Media Magnification

The way in which the media report on terrorism, and whether that affects individual behaviour, is both highly sensitive and controversial. Research by Kearns, Betus and Lemieux (2017) found that terrorist attacks by a Muslim perpetrator attract on average about 4.5 times more media coverage, controlling for a number of characteristics. They find that U.S. media outlets disproportionately emphasise the smaller number of terrorist attacks by Muslims - leading them to argue Americans to have an exaggerated sense of jihadi terrorism threat. These

[10] Note also that, in the column (4) specification, for the recent attacks there are strongly significant pre-trend coefficients, being positive and significant at t-1 and t-3 and negative and significant at t-2. This is because of the closeness of the final two attacks in Manchester (22nd May 2017) and London Bridge (3rd June 2017).

notions are backed up in other work on the economics of terrorism – see, for example, the discussion by Krueger (2007).[11] Other research empirically studied individuals' exposure and reaction to crime-related media (for example, Surette, 2013), with debates about whether it is exposure to media coverage of violent crimes that triggers human aggression or whether individual reactions are more in line with copycat behaviour. Both of these, whilst being contested hypotheses amongst criminal justice scholars, emphasise a role of media in altering crime propensities of individuals and groups in society.

According to these lines of argument, media could play a role in sustaining the post-terror attack jumps in local hate crime that the results of the previous section of the paper showed. It is of considerable interest in trying to look at possible mechanisms that drive these results to consider a possible role of media reporting on jihadi terrorism inducing attitudinal change in perceptions of Muslims in society that could result in more anti-Muslim hate crime.

The ten terror attacks studied in this paper received significant newspaper coverage. This can be confirmed by assembling data on the number of articles in the UK media that report on terrorist attacks committed by Islamist or jihadi groups.[12] For the entire population of articles published online or in print in UK national newspapers from April 2008 to August 2018, a keyword search was run on LexisNexis using the following algorithm: "(terror or terrorist or terrorism) AND (attack or bomb or bombing or incident) AND (muslim or islam or islamist or jihadi or isil or al-qaeda or isis or islamic state)". Figure 3 reports the most common words in the headlines of the articles our search returns. Figure 4 very much confirms that in weeks where the terror attacks occurred, so was the newspaper coverage higher, and that the peaks in

[11] Other research areas also study connections between media and crime, sometimes with connections to terrorism. For example, Surette, Hansen and Noble (2009) study how terrorist groups themselves have different degrees of media orientation. A large body of research has considered exposure to media violence and its connections to violent aggression (see, *inter alia*, the meta-study of Savage and Yancey, 2008, or the movie violence paper of Dahl and DellaVigna, 2009) and also to criminal behaviour more generally (see, *inter alia*, Ferguson and Savage, 2012, Doley, Ferguson and Surette, 2013 or Rios and Ferguson, 2019).

[12] Some selected examples of media coverage, from both national and local Manchester newspapers, are shown in the Appendix.

articles about jihadi terrorism correspond to the jihadi terror attacks which either occurred in Western Europe or whose victims where British citizens.

*Including Media in the D-i-D Analysis*

Inclusion of weekly media coverage measures in the D-i-D specifications of the previous section of the paper also shows a significant covariation between Islamophobic hate crime and media. Table 5 reports D-i-D estimates looking at media measures: the weekly number of articles on jihadi terrorist attacks, and the number of peak articles defined via a dummy variable set equal to one when the number of articles published falls within the top 5% of the distribution. As the results in the Table show, there is a positive and statistically significant association between the media measures and the number of Islamophobic hate crimes and incidents. More media coverage is connected to a higher rate of Islamophobic hate crime. In the week of the peak in newspaper articles, there is a sizable percent increase of Islamophobic hate crimes and this persists in the following two weeks, decreasing in size.[13] There are no significant effects in the weeks preceding it.

*Media magnification of local hate crime*

To hone in more, one can move to look at daily patterns in the number of hate crimes and incidents reported to GMP and number of newspaper articles reported in UK national newspapers. We study the dynamics of the two time series, both to better understand the granular detail of the timing of their co-movements through data visualisation and to probe relevant questions regarding the direction of causality.

To begin the data visualisation process, Figure 5 reproduces the earlier D-i-D analysis on the daily data. In a specification comparable to the event study reported in column (5) of Table 2, but with estimates reported for the 7 days before and after the attack, an interesting

[13] The point estimates in the following weeks prove to somewhat less stable. This likely occurs as headline news in UK newspapers is often followed by the same topic being frequently reported on in the following week too (so one might observe successive Peak Articles).

pattern emerges. The pre-attack coefficients are all insignificant, showing there to be no violation of the parallel trends assumption underlying the D-i-D estimator. The post-attack coefficients show a highly interesting pattern of heterogeneity that speaks strongly to the media magnification idea. All are positive and significant, but the initial sizable spike up on the day of the terror attack is followed by even higher Islamophobic hate crime in the next few days, after which the estimates decay a little. In the following week they return to the (higher than pre-attack) level seen on the day of the attacks. These patterns are clearly in line with a narrative that some of the Islamophobic hate crime activity may not be an immediate response, but rather is stimulated by information on perpetrators and victims highlighted in media activities in days following attacks.

To see this pattern even more clearly and to look at the media variable at the same time, Figure 6 plots the daily time series of the number of Islamophobic hate crimes in Manchester (the dotted line with scale shown on the right y axis) and the number of newspaper articles (the solid line with scale shown on the left axis) for the Lee Rigby, Charlie Hebdo, Paris (November 2015) and Brussels (March 2016) attacks in a time window two weeks before and after attacks. The charts make it quite clear that peaks in Islamophobic hate crimes and incidents occurred after the peak of media coverage in the first few days following the terror attacks.

The temporal patterns of change therefore show that Islamophobic hate crimes spike up straight away, but then with a lag they go higher. The media measures also occur with a lag (typically appearing in the newspapers late on the day and more visibly to the general public the day after). At first glance, this dynamic seems in line with causality running from media to hate crime, rather than the other way around. To test this more formally and to see whether media exacerbates the effect of jihadi terrorist attacks on Islamophobic hate crimes and incidents, it is possible to set up Granger causality tests on the two daily time series.

In a general sense, a variable x that evolves over time is said to Granger-cause another variable y if predictions of the value of y based on its own past values and on the past values of x are better than predictions of y based only on its own past values (see the original formulation in Granger, 1969). Specifically, this can ascertained by testing the joint significance of J lagged y's and x's in the following dynamic time series model (where v is a white noise error term):

$$y_t = \theta_0 + \sum_{j=1}^{J} \theta_j \, y_{t-j} + \sum_{j=1}^{J} \lambda_j \, x_{t-j} + v_t \tag{5}$$

Granger causality tests can be computed separately for the two possible directions of causality, running from Media to Islamophobic hate crime and from Islamophobic hate crime to media. For each of these, setting J = 5 in daily data and estimating separately for the ten terror attacks with a time series window of 30 days either side of the relevant attack, Table 6 reports p-values from the Wald statistics testing the null hypothesis that all coefficients on the five lags of variable x are jointly zero in the equation for variable y. The evidence is much more in line with the notion that newspaper coverage Granger-cause Islamophobic hate crimes and incidents, rather than the other way around. Indeed, this seems to be very much the case in the aftermath of most of the terrorist attacks. For Lee Rigby, Charlie Hebdo, Tunisia, Paris, Manchester and London Bridge the p-values are all significant at 1% level. Brussels is also strongly significant with a p-value of 0.027. For all attacks, the null of causality running from Islamophobic hate crime to media cannot be rejected. Thus, the balance is very strongly in favour of causality running from media to hate crime. It seems that media coverage exacerbated local Islamophobic hate crimes and incidents in the aftermath of the attacks as news diffused to possible hate crime perpetrators.

*Terror attacks featuring less UK media coverage*

One further observation of interest is that some terrorist attacks - for one reason or another - receive less media attention. Take, for example, the case of three significant terror attacks that did not meet the criteria for inclusion in our sample. They took place further away from the UK (i.e. not in Western Europe) in 2016 and 2017: the 01 January 2017 attack in Istanbul that resulted in 39 deaths (and 70 injuries); the 28 June 2016 attack in Istanbul Ataturk Airport (45 deaths, 230 injuries); and the 03 April 2017 St. Petersburg attack (15 deaths, 87 injured). None of the total of 99 deaths were from Western Europe. In these three incidents, the victims were predominantly Russian or Turkish nationals. [14] The perpetrators were jihadis from either Uzbekistan or Kyrgyzstan.

Despite featuring many more deaths and injuries than most of the ten attacks considered in the prior analysis, all three of these received much less substantial media attention in UK newspapers. This is shown in the upper panel of Figure 7, which shows daily media coverage of the ten attacks already studied (in black) and the same for these additional three attacks (in grey). Interestingly, in line with the ten attacks media coverage does increase on the attack day, albeit by less. Importantly, it does not rise anywhere near as much in the three days following when the media coverage of the ten attacks surged.

The lower panel shows what happened to Islamophobic hate crime in Manchester, presenting event study D-i-D estimates for these three attacks in analogous way to the earlier analysis. For these, there is no spike in anti-Muslim hate crime in Manchester and no media induced magnification afterwards. Interestingly, these attacks that were featured less by the media do not seem to generate local hate crime spikes in Manchester.

## 6. Victims and Perpetrators

Over the investigation period, there were 2,522 Islamophobic crimes and incidents recorded in the Greater Manchester area. Some directly followed terrorist attacks, and disproportionately so as the spikes up discussed earlier showed, but others appear to be

[14] Of the total of 99 deaths, 49 were Turkish or Russian. One person had dual French and Tunisian nationality, and there was one Canadian. The remainder (except for two from Morocco) were all of Asian nationality.

unprovoked. The extremely rich data enables a more detailed study in terms of the nature of the hate crimes themselves, the spatial distribution of hate crimes, and the characteristics of both victims and offenders.

*The Nature of Hate Crimes*

Islamophobic hate incidents and crimes form a sub-group of the wider ‘Hate’ category. Over the period from 1st April 2008 to 31st July 2018 there were in total 54,809 incidents that were classified as hate incidents, out of which 79 percent were hate crimes (43,231). Within this sample, there was a total of 2,522 Islamophobic hate crimes and incidents occurring, out of which 76 percent (1,924) were classified crimes. Hence, the fraction of Islamophobic hate crimes to overall incidents is comparable with the wider (and much larger) hate category. Looking further into the types of Islamophobic hate crimes, the majority of them are classified as a public order offence (60 percent), criminal damage and arson (13 percent), violence without injury (18 percent), and violence with injury (6 percent).

*Spatial Distributions*

The location of the incident was geocoded to geographic Census units at the lower super output area (LSOA). There are 1,671 LSOAs under the geographical remit of the Greater Manchester Police. Of these, almost 50 percent of LSOAs had no hate crimes and incidents occurring over the entire period, while in the top 5 percent of LSOAs there were between 6 and 44 hate crimes and incidents. Hence, Islamophobic hate crimes and incidents are highly concentrated. This is shown visually in the map in Figure 8. Moreover, this concentration is strongly associated with the concentration of the Muslim population in an area, as depicted in Figure 9. A Spearman rank correlation between the number of Islamophobic hate crimes and the Muslim population across LSOA’s is 0.51 (p-value = 0.00). Very clearly, Islamophobic hate crimes disproportionately occur in the neighbourhoods where Muslims live.

Moreover, it is possible to utilise machine learning methods to ascertain more generally what are the most important spatial dimensions in terms of socio-demographic predictors of Islamophobic hate crimes and incidents. The machine learning approach is superior to more conventional methods. First, when there are a very large number of predictors and theory is not forthcoming on prioritising which to investigate machine learning based model selection tools become useful. Second, taking a non-theoretical approach to pick favourite predictors in an ad hoc manner is not desirable. Third, it permits the generation of (out of sample) predictions of potential Islamophobic hate crime and incidents hotspots.

Methodologically, we use a tree-based random forest model. Figure 10 reports the list of variables that led to the largest average reduction in the residual sum of squares (RSS) across the bootstrapped samples. This establishes that Islamophobic hate crimes and incidents occur in less densely populated suburban areas with a higher share of Arab and Muslim populations (and lower British and White populations). These areas are characterised by worse levels of social deprivation – including higher long-term unemployment, higher frequencies of single households, methods of commuting, heating, amongst others.

*Perpetrators*

Having access to offender data allows for a novel study of the characteristics of perpetrators of Islamophobic hate crime offender. For around 20 percent of cases data is available on at least one offender. In total 473 offenders committed 416 Islamophobic hate crimes. This is comparable to the average rate for all crimes for GMP with an offender detection rate of 23 percent. For 80 percent of the 473 offenders the offender data includes their approximate home address in form of an Output Area (OA) reference.[15] Knowing the Output Area of the home address offers some understanding of the socio-economic characteristics of the offender.

[15] There are 8,683 OAs in Greater Manchester.

Figure 11 plots the spatial concentration of Islamophobic hate crime offenders. The data visualization shows that offenders are concentrated in certain areas of Greater Manchester. These are generally deprived areas outside the city centre, close to the vicinity of neighbourhoods with a higher share of Muslims, but not the same places. Table 7 shows a comparison of the characteristics of offenders of Islamophobic hate crime with all other hate crime offenders and all offenders. They are older and more likely to be white. Interestingly, on average they commit crimes in slightly larger groups than other types of crimes (as suggested by theoretical modelling of hate crime perpetrators, for example by Craig, 2002).

Finally, the available data also permits study of connections between where perpetrators live and where they commit crimes. Figure 12 plots the distribution of the distance between the home address of the 375 offenders of Islamophobic hate crime and the location of the hate crime. Whilst 60 percent of offenders live within 2km of the location of the committed hate crime, they tend not to live in the neighbourhoods of their victims, but in the neighbouring boroughs, with the mode distance being 1km away.

## 7. Conclusions

This paper reports empirical findings that connect the occurrence of international jihadi terror attacks to hate crimes committed against Muslims in a local setting and far away from where the attacks took place. Event study analysis of the impact of ten international attacks on local hate crime in Manchester reveals there to have been an immediate big spike up in Islamophobic hate crimes and incidents following the attacks. Importantly, their higher incidence was subsequently magnified by the nature of media coverage in national newspapers. The mechanism underpinning this is that potential perpetrators are induced into committing hate crimes by the media coverage. The media induced magnification subsequently attenuates, but hate crime incidence cumulates to higher levels than prior to the series of ten attacks.

Anti-Muslim hate crimes occur more in socially deprived areas with a high Muslim population, and are spatially concentrated. Perpetrators, however, are typically older and more likely to travel to places other than where they live to commit hate crimes. The overall conclusion is that, even when they reside in places far away from where jihadi terror attacks take place, local Muslim populations face a media magnified likelihood of hate crime victimization that occurs following international terror attacks. These findings are likely to have had important effects on community cohesion in Greater Manchester, and hold ramifications for the future. Furthermore, the nature of the media magnification means the results are of wider significance for other localities with ethnic groups who are potential victims of Islamophobic hate crime.

That hate crime is exacerbated by media coverage poses a number of important questions about handling and consequences of politically sensitive events. First, it is clear that these crimes impose significant economic and social costs when they occur both on individual victims and on their communities. Second, with hate crime levels and the threat of victimization being higher, these costs are likely to increase, and to further fragment and alienate minority communities in the medium to longer term if the responses to withdraw back into communities seen elsewhere also happen (as documented for US states in Esteban and Klor, 2016). Third, and to conclude, there are issues for wider society about how the media go about their business of reporting on terror attacks and whether current practice, especially of a more sensationalist and antagonistic nature, is indeed appropriate or whether it should be more carefully monitored and better regulated in future. This big challenge applies to both conventional newspapers and more broadly to online coverage by media and other pressure groups, including through the usage of different forms of social media. These cyber dimensions very obviously form an important research agenda for the future.

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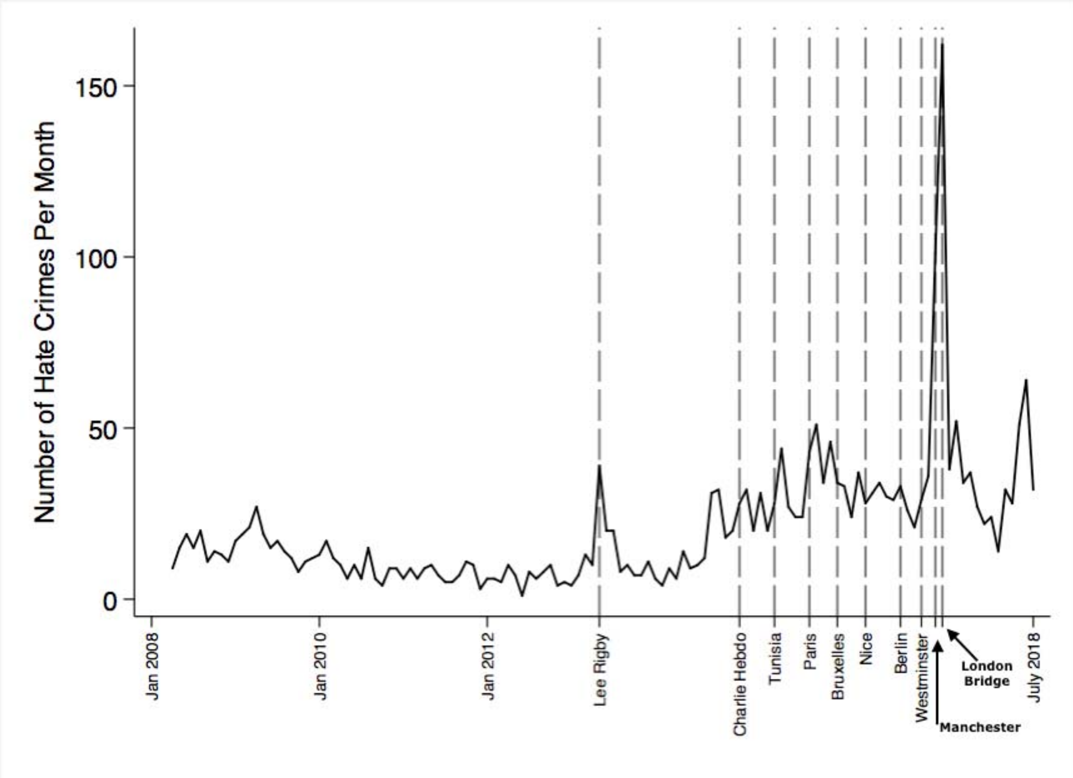
**Figure 1: Islamophobic Hate Crimes in Manchester**

(a) Monthly - April 2008 to July 2018




(b) Weekly - 2017

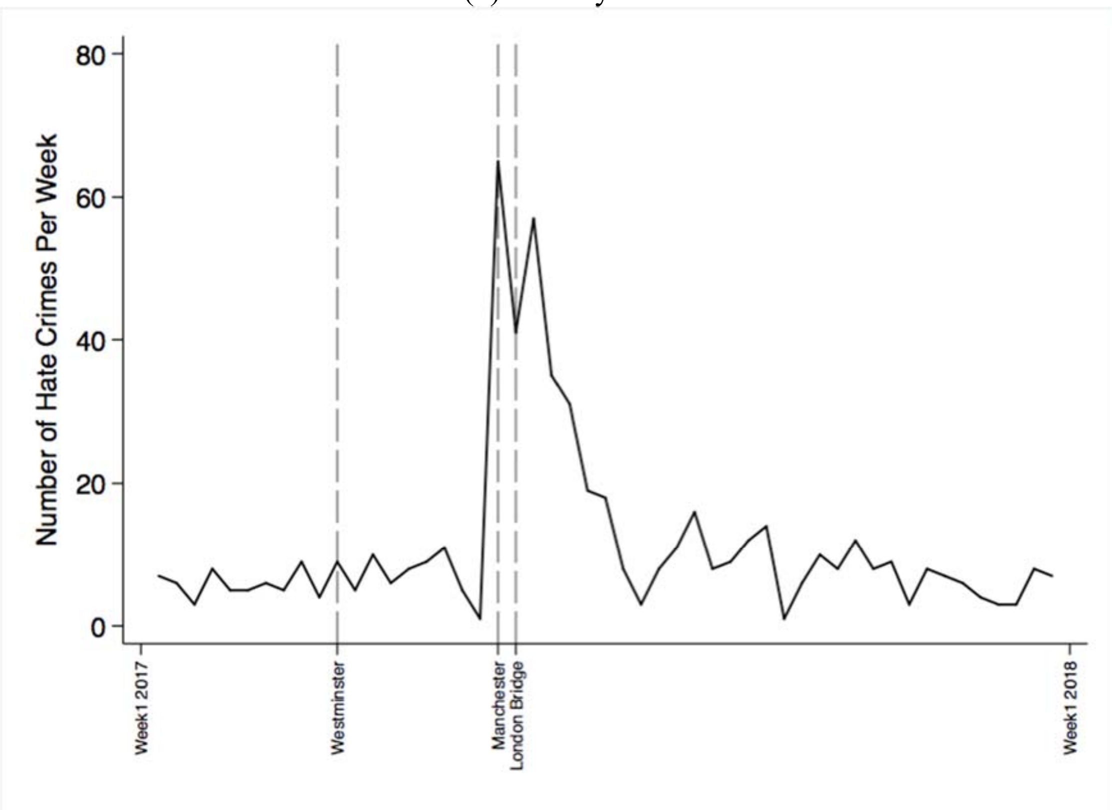
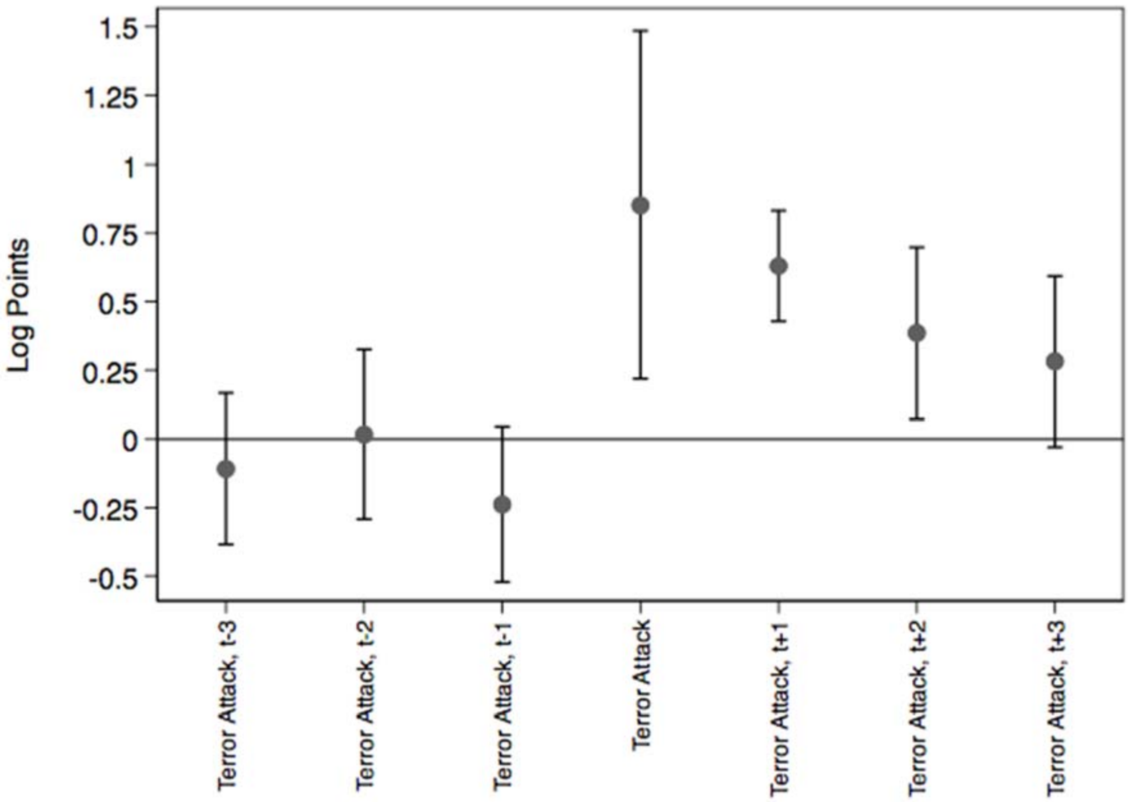


**Figure 2: The Effect of a Jihadi Terrorist Attack on Islamophobic Hate Crime, 3-Week Leads and Lags**




Note: Coefficients and their 95% confidence intervals taken from the specification in column (5) of Table 2.

**Figure 3: Word Frequency in Headlines of Articles Describing Jihadi Attacks in UK National Newspapers**

a) Word cloud of 150 most common words


b) Occurrence of most common words

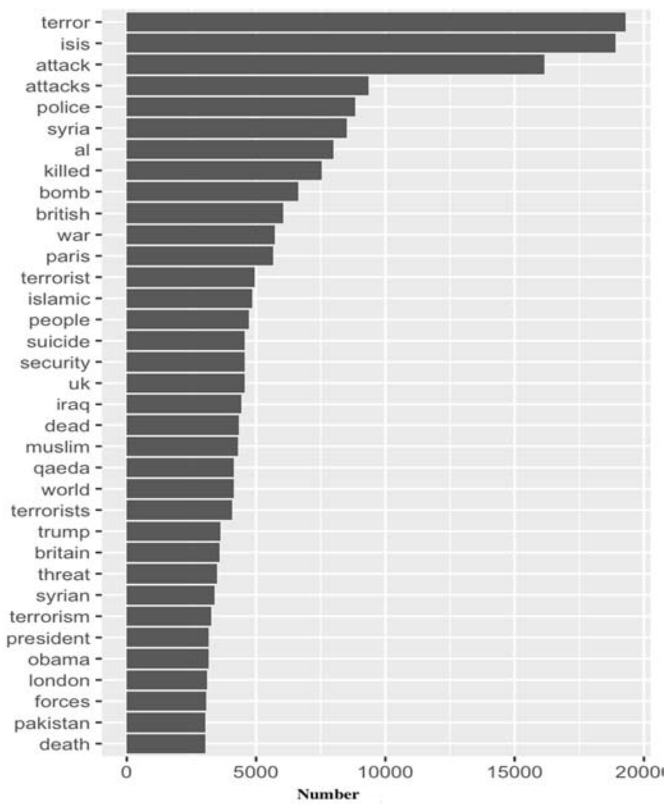
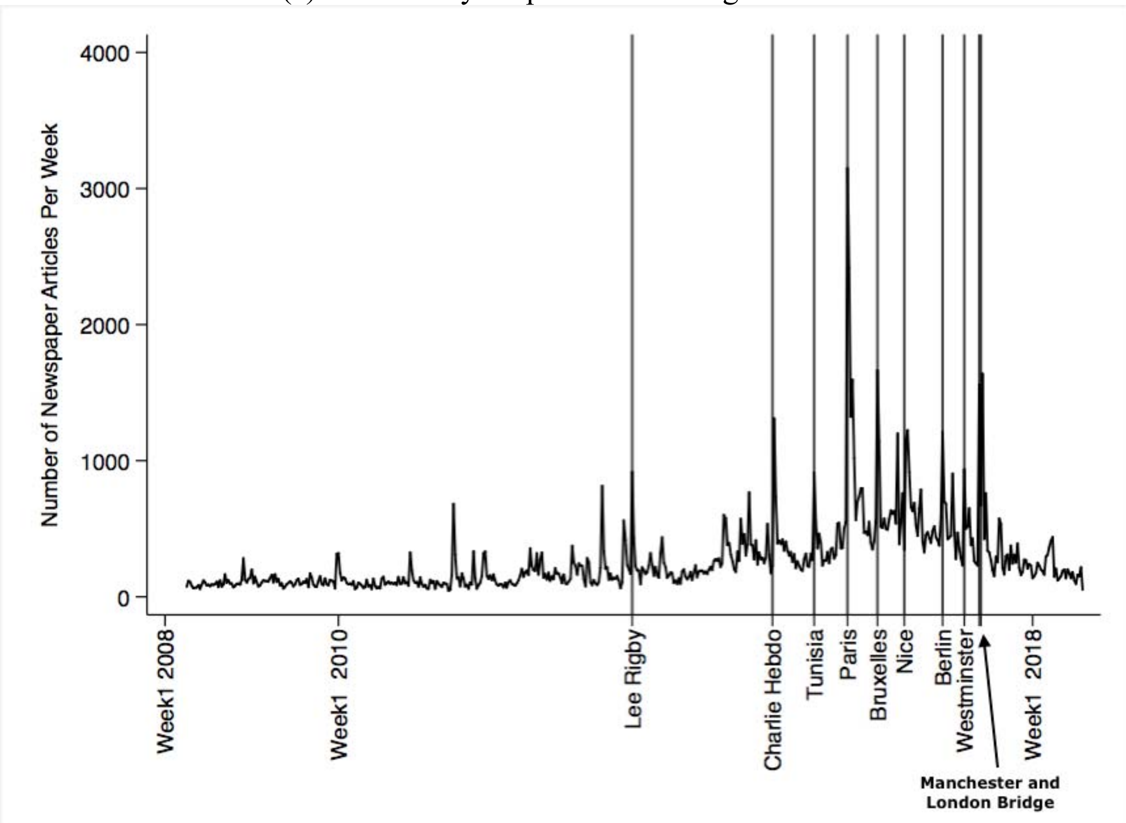


**Figure 4: Weekly Number of Newspaper Articles Published in UK National Newspapers on Jihadi Terror Attacks, 2008 to 2018**

(a) Weekly - April 2008 to August 2018




b) Weekly - 2014 to 2018

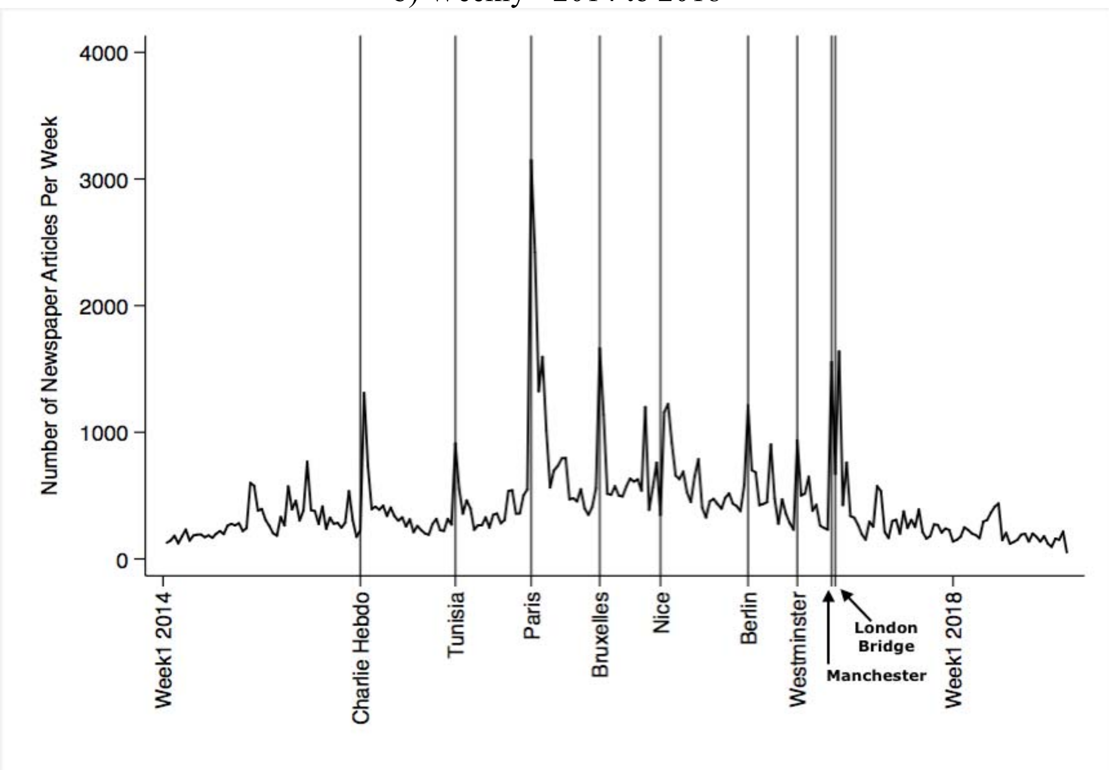
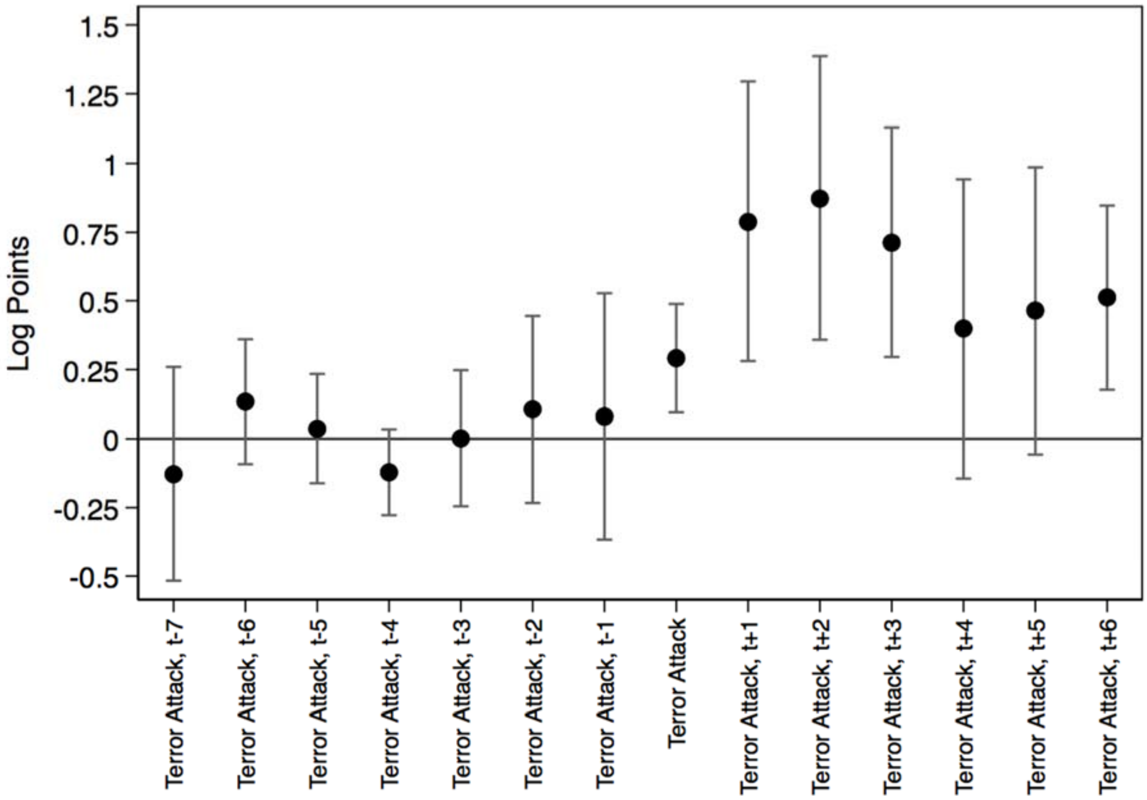


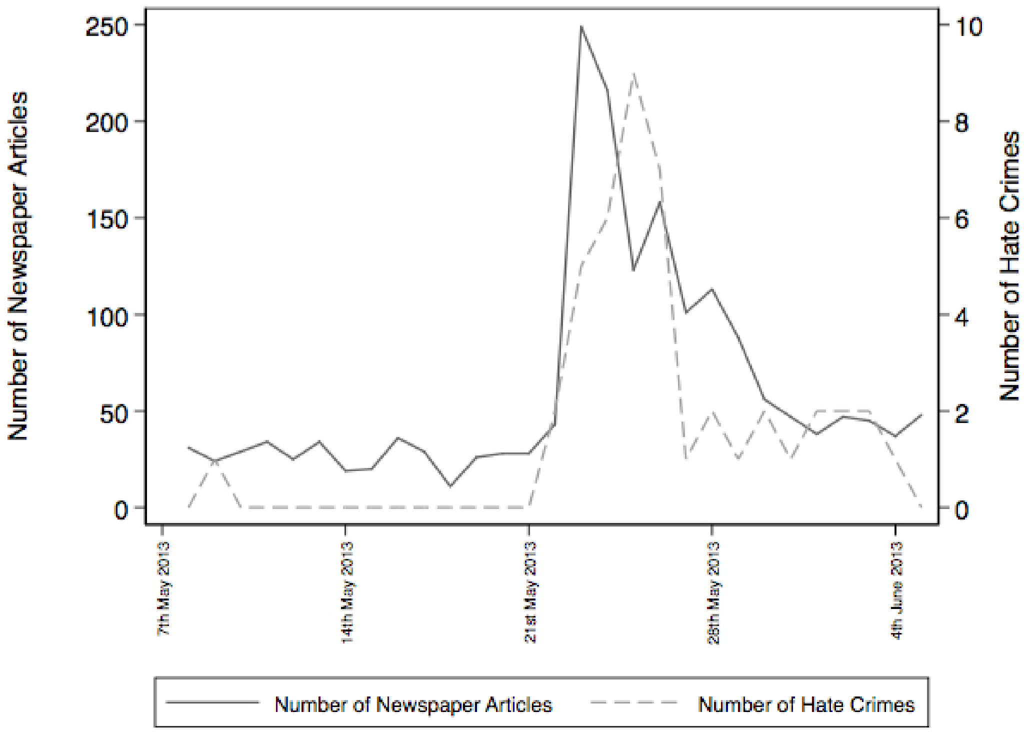
**Figure 5: Daily Islamophobic Hate Crime and Terror Attacks, Seven Days Leads and Lags, in Logs**



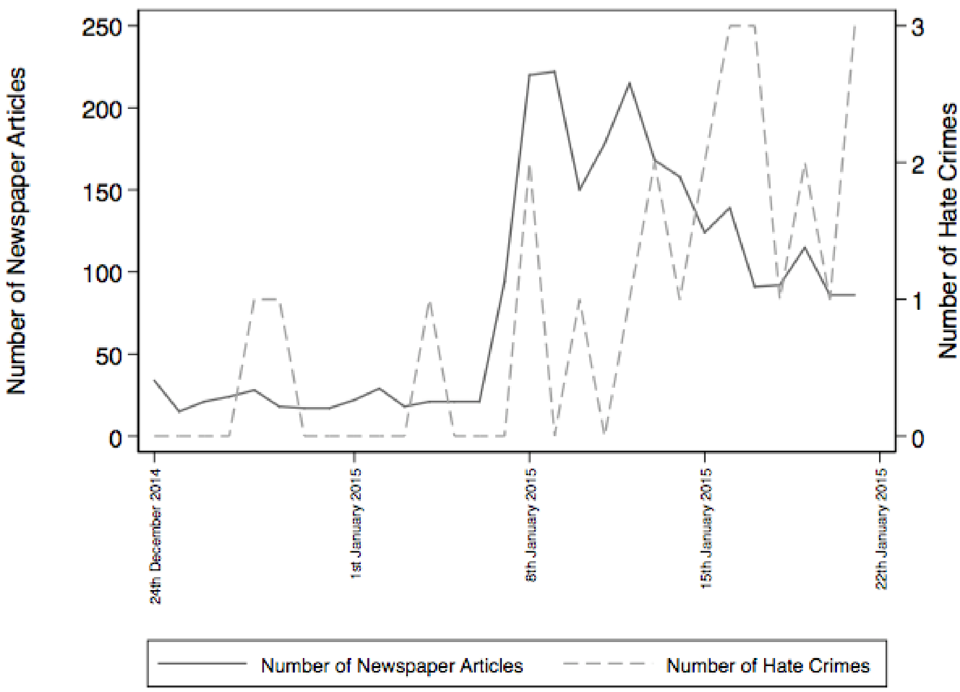

Note: Coefficients and their 95% confidence intervals from a specification comparable to column (5) of Table 2 but based on daily data and estimating event study effects in a seven day window around attack days.

**Figure 6: Daily Numbers of Islamophobic Hate Crimes and Newspaper Articles, Two Weeks Preceding and Following a Jihadi Terror Attack**

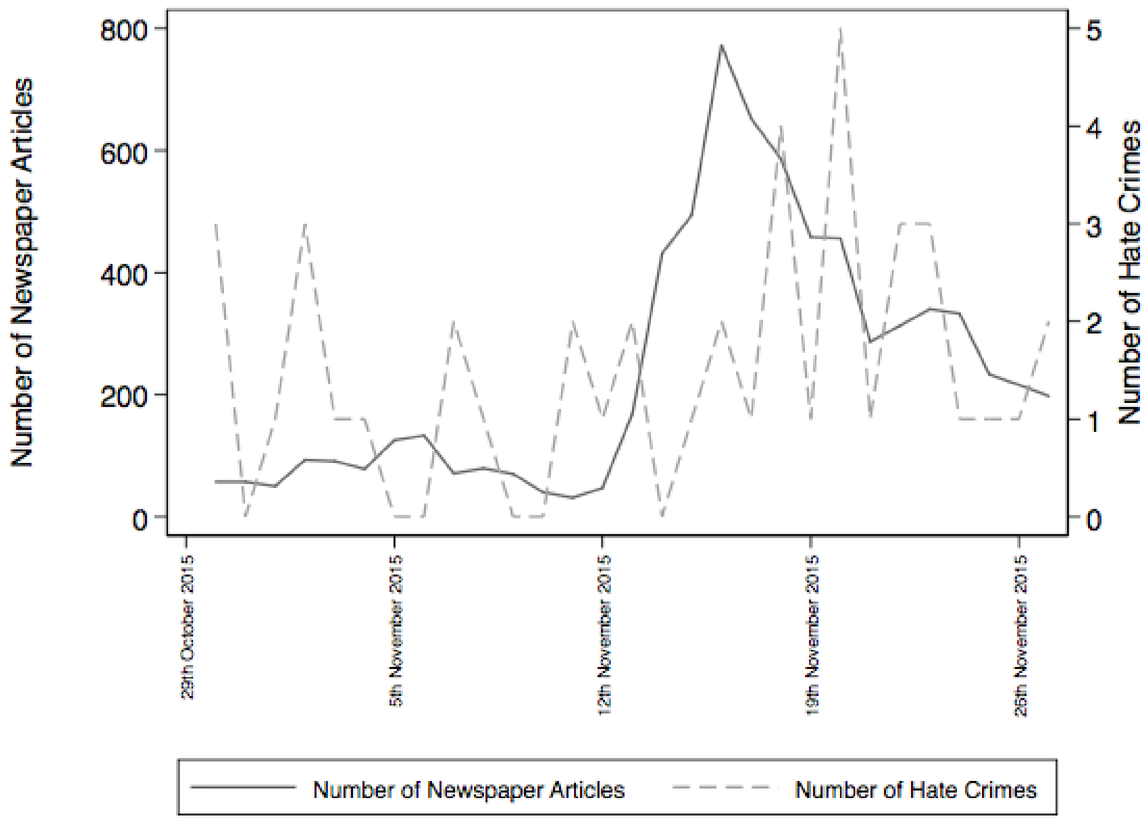
a) Lee Rigby (22nd May 2013)




b) Charlie Hebdo (7th January 2015)



c) Paris (13th November 2015)




d) Brussels (22nd March 2016)

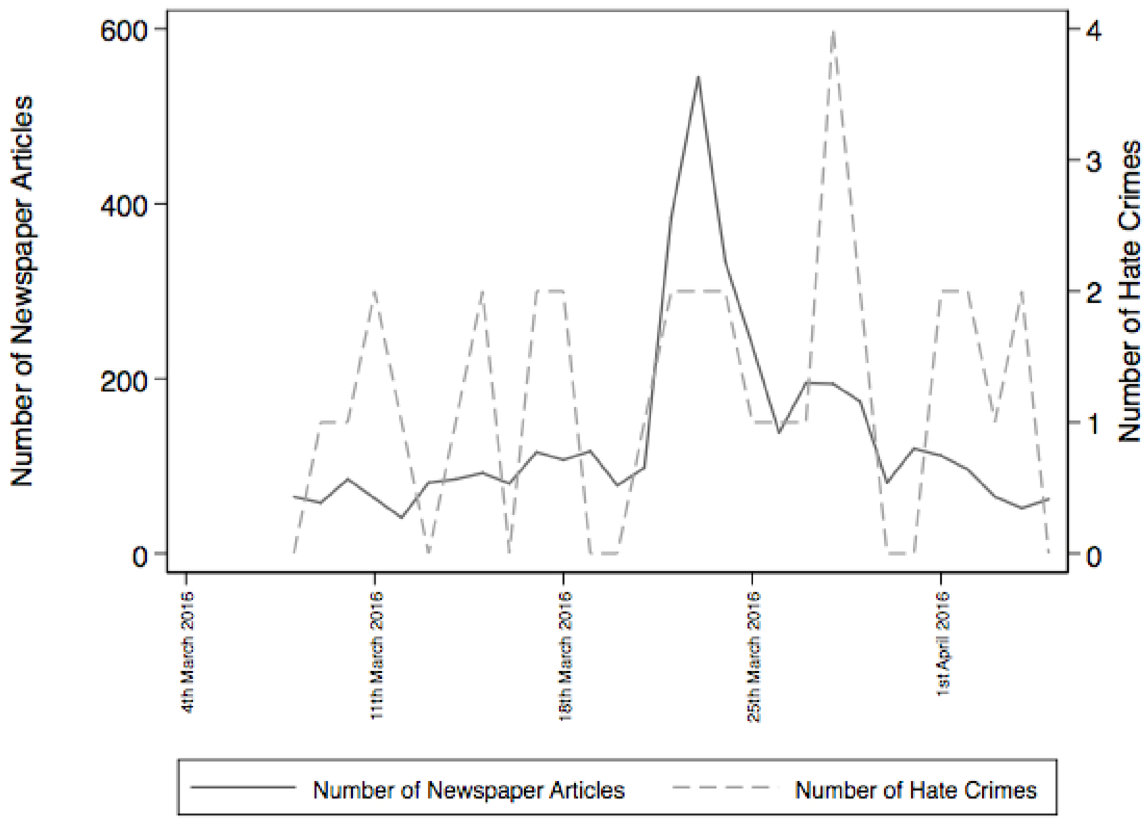
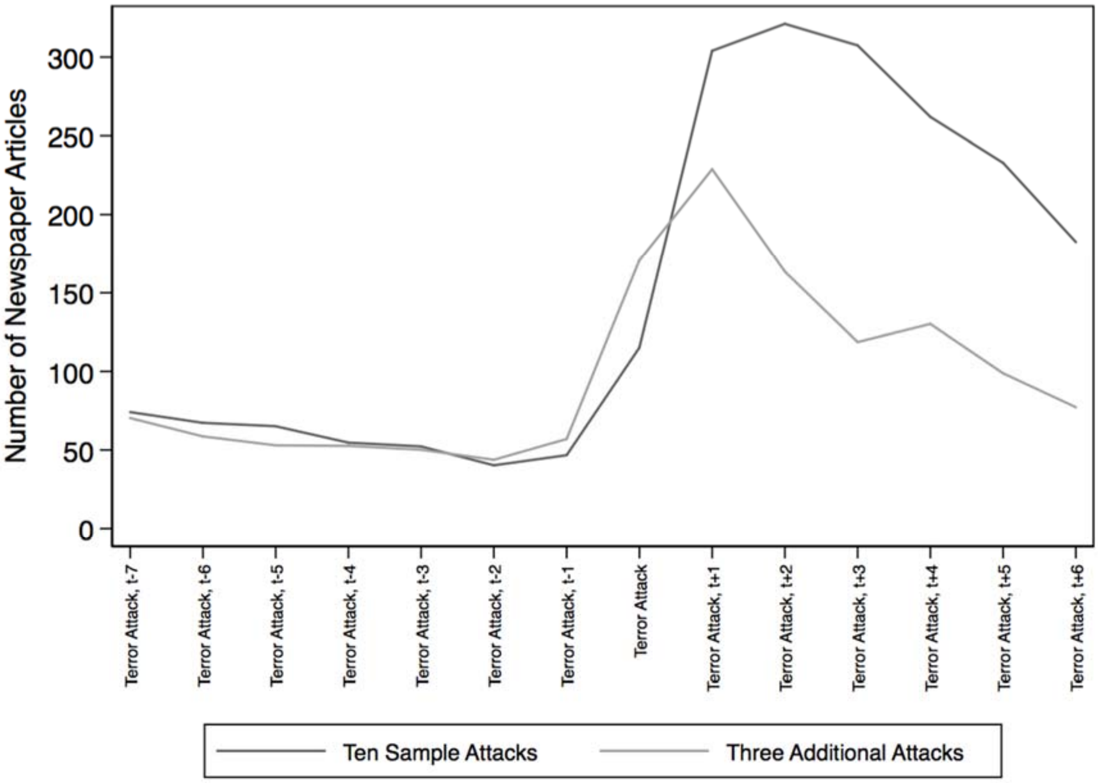


**Figure 7. Three Additional Terror Attacks**

a) Media, daily news articles




b) Islamophobic hate crime, three additional attacks

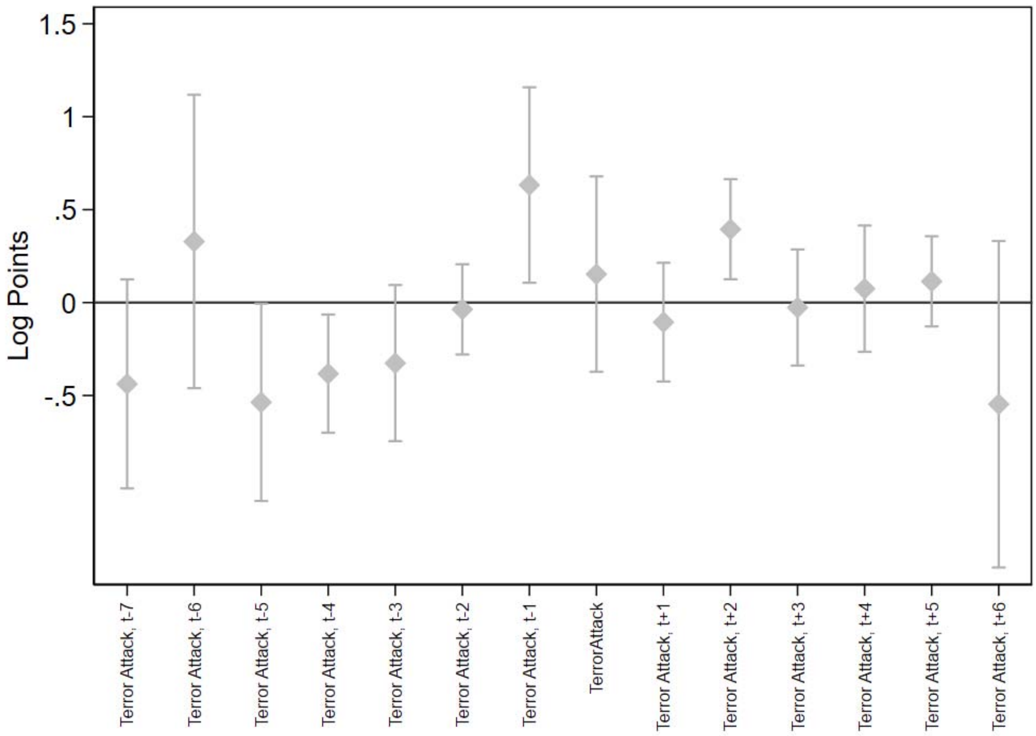
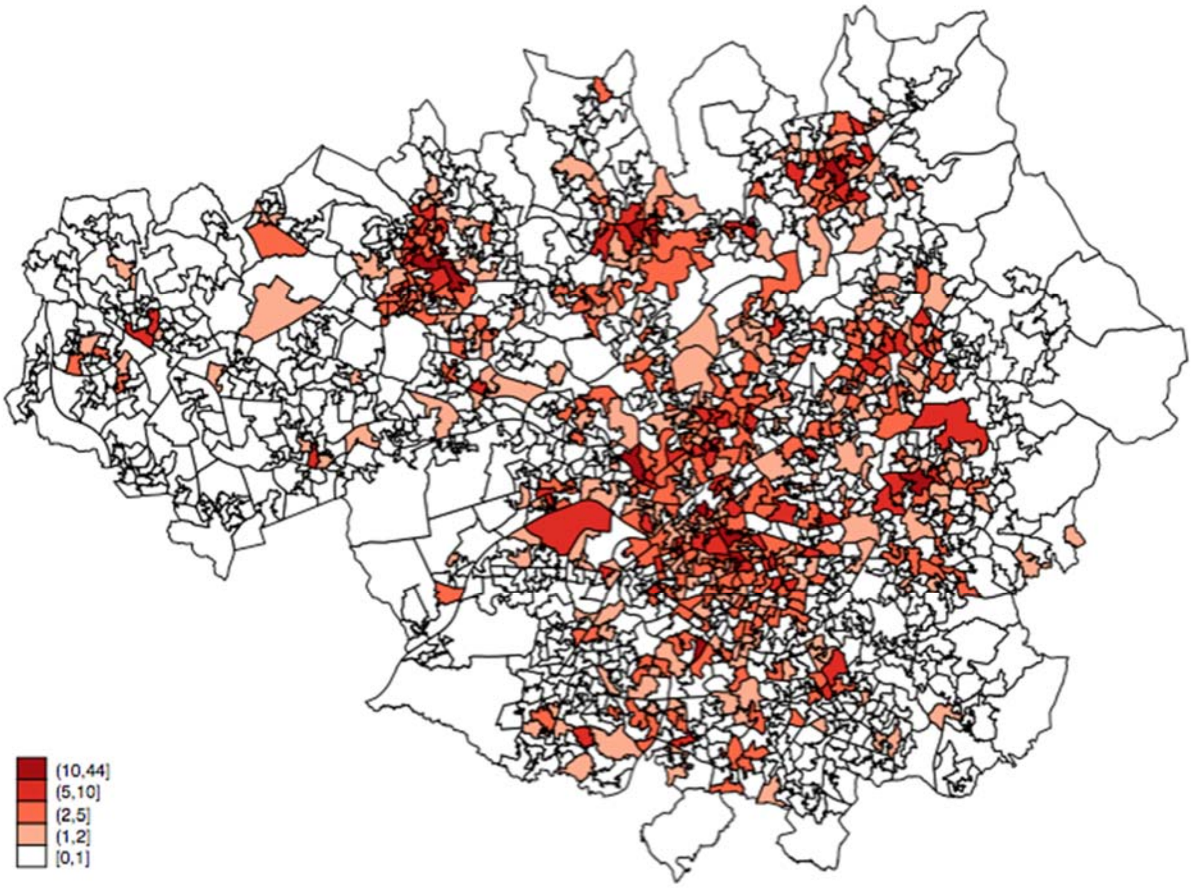
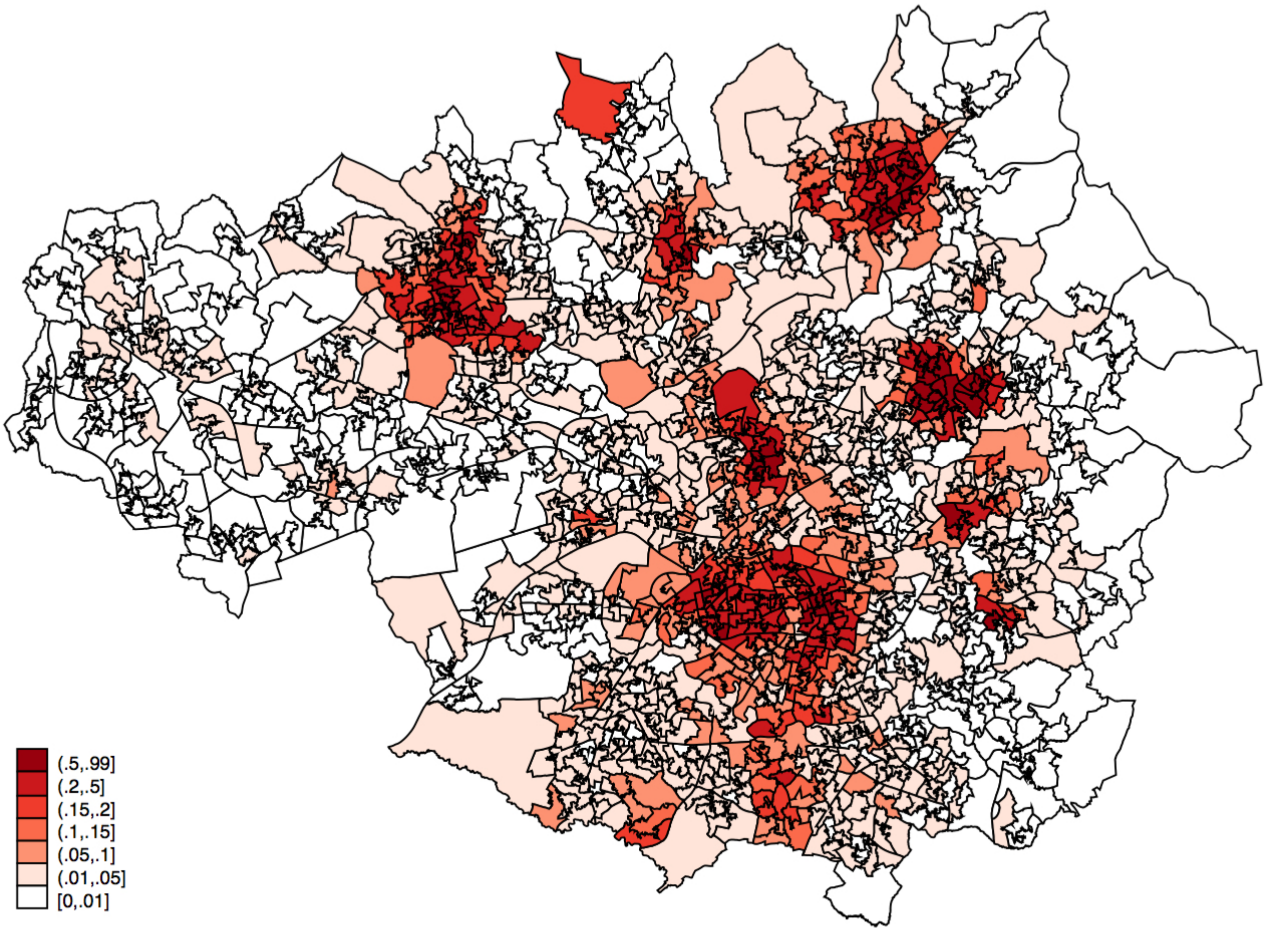


**Figure 8: Distribution of Islamophobic Hate Crimes, by Lower Super Output Area**



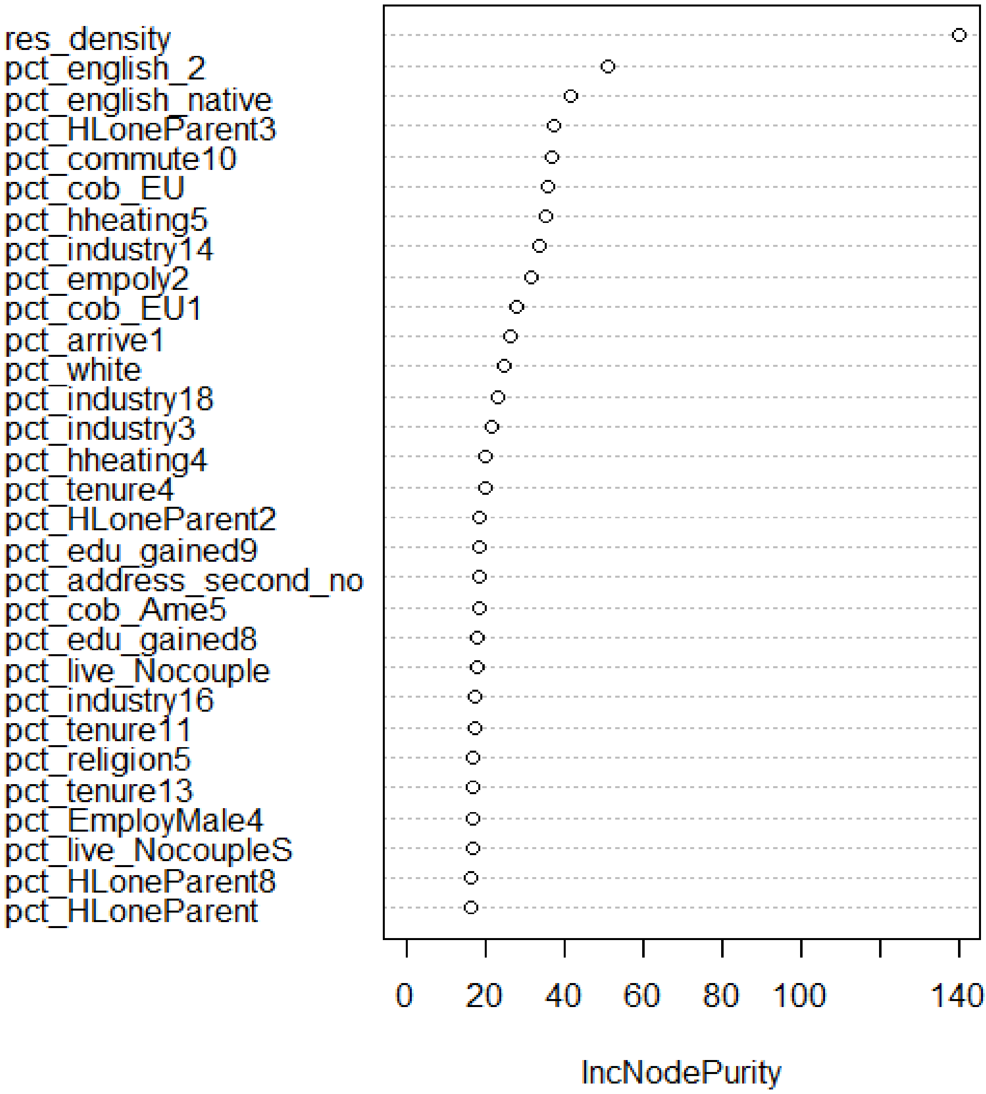

Note: Map shows the total number Islamophobic hate crimes reported in 2008-2018 across Lower Super Output Areas (LSOAs) in Greater Manchester.

**Figure 9: Percent Muslim population, by Lower Super Output Area**



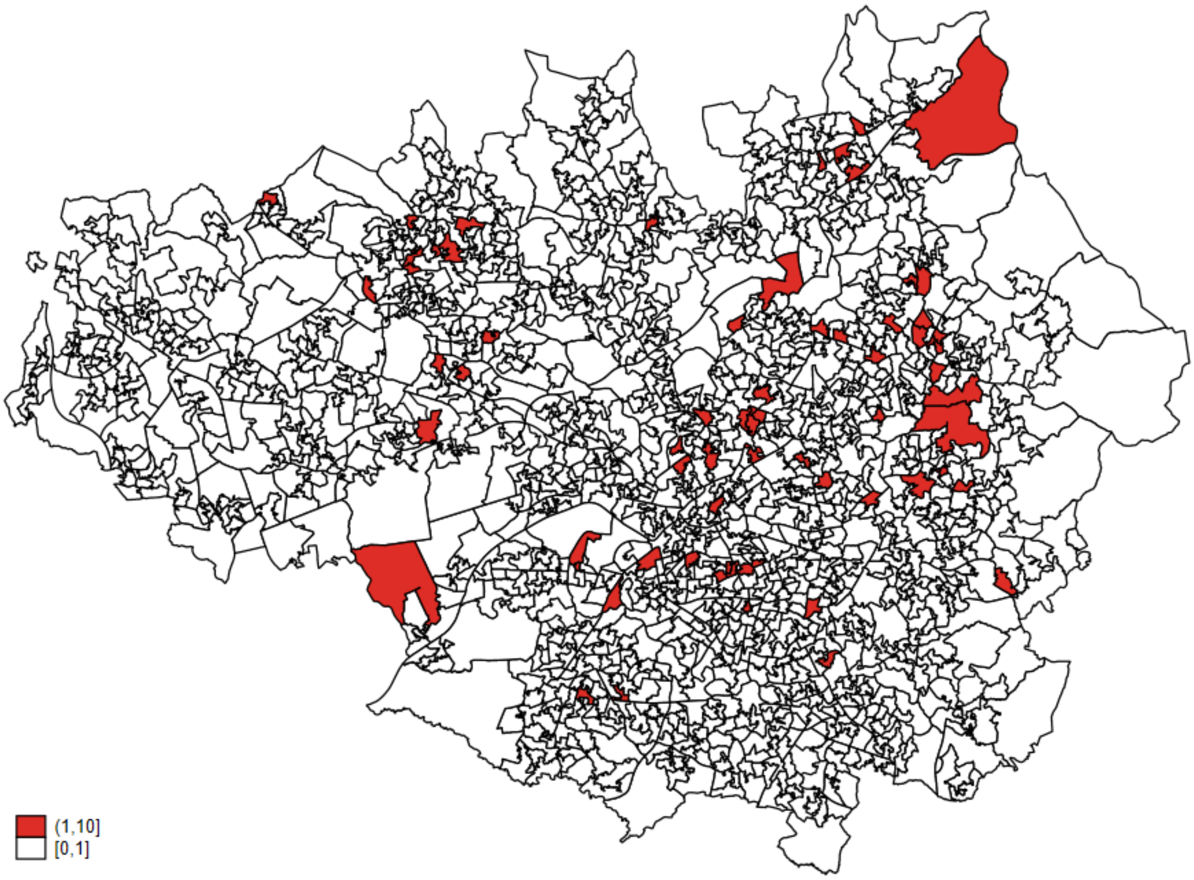

Note: Map shows the percent of Muslim population across Lower Super Output Areas (LSOAs) in Greater Manchester, as reported in the 2011 England and Wales Census.

**Figure 10: Random Forest Predicting Crime Location**




Note: Figure shows in descending order the variables that led to the largest average reduction in RSS across the bootstrapped samples as explained in Section 6. To find the most important socio-demographic predictors that characterise the geographic areas where Islamophobic hate crimes and incidents occur, all variables reported in the 2011 England and Wales Census were used. All are expressed relative to the number of residents within the area. The following list describes the list in descending order: density, percent of persons whose main language is not English , percent of persons whose main language is English , percent of households with lone parent not in employment, percent of persons who commute on foot, percent of persons whose country of birth is European, percent of persons with solid fuel heating, percent of persons working in support service activities, percent of persons working full-time, percent of persons born in the UK, percent of persons that are white, percent of persons working in other industries, percent of persons working in manufacturing, percent of households who have oil heating, percent of persons whose house is socially rented from council, percent of households with lone parent in full-time employment, percent of persons with maximum education, percent of persons with no second address, percent of persons whose country of birth is in South America, percent of persons not living in a couple, percent of persons working in Education, percent of persons whose house is privately rented from relative or friend of household member, percent of persons whose religion is Muslim, percent of persons living rent free, percent of male unemployed, percent of persons not living in a couple and are single, percent of households with female lone parent, percent of households with lone parent.

**Figure 11: Residency of Offenders**




Note: Map shows the number of offenders of anti-Muslim hate crimes reported in 2008-2018 across Lower Super Output Areas (LSOAs) in Greater Manchester. Each offender was matched to an LSOA using the Output Area of their home address.

**Figure 12: Distance Between Home Address of Offender and Location of Hate Crime**


Note: Figure shows the distribution of the distance between the home address of the offender and the location of the hate crime. Distance to crime is in kilometres.

### Table 1: Summary Statistics, April 2008 to August 2018

| | Weeks | Mean |
|---|---|---|
| **A. Sample statistics** | | |
| Terror attack incidence | 538 | 0.02 |
| Islamophobic hate crimes | 538 | 4.69 |
| Disabled hate crimes | 538 | 4.09 |
| Antisemitic hate crimes | 538 | 3.40 |
| Sexual orientation hate crimes | 538 | 10.80 |
| **B. Terror and non-terror attack weeks** | | |
| Islamophobic hate crimes \|Terror attack ($H_1$) | 10 | 19.40 |
| Islamophobic hate crimes \| No terror attack ($H_0$) | 528 | 4.41 |
| Non-Islamophobic other hate crimes \|Terror attack ($O_1$) | 10 | 21.40 |
| Non-Islamophobic other hate crimes \| No terror attack ($O_0$) | 528 | 18.23 |
| **C. Gaps** | | |
| Difference in Islamophobic hate crimes [$H_1 - H_0$] | 538 | 14.99 (1.67) |
| Difference in non-Islamophobic hate crimes [$O_1 - O_0$] | 538 | 3.17 (3.09) |
| Difference in differences, [$H_1 - H_0$] – [$O_1 - O_0$] | 538 | 11.82 (2.67) |

Notes: Weekly counts of hate crimes for the four crime types (Islamophobic, Disabled, Antisemitic, Sexual orientation) in 538 weeks between April 2008 and August 2018. Standard errors in parentheses.

## Table 2: Hate Crimes and Jihadi Terror Attacks

| | Log (Hate Crimes) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| [Islamophobic X Terror attack], t+3 | | | | 0.388 | 0.281 | 0.166 |
| | | | | (0.162) | (0.154) | (0.146) |
| [Islamophobic X Terror attack], t+2 | | | | 0.480 | 0.385 | 0.282 |
| | | | | (0.162) | (0.155) | (0.151) |
| [Islamophobic X Terror attack], t+1 | | | | 0.735 | 0.630 | 0.522 |
| | | | | (0.113) | (0.100) | (0.137) |
| [Islamophobic X Terror attack] | 0.990 | 0.836 | 0.751 | 0.959 | 0.851 | 0.751 |
| | (0.300) | (0.316) | (0.294) | (0.289) | (0.314) | (0.299) |
| [Islamophobic X Terror attack], t-1 | | | | -0.168 | -0.238 | -0.393 |
| | | | | (0.164) | (0.141) | (0.143) |
| [Islamophobic X Terror attack], t-2 | | | | 0.090 | 0.017 | -0.163 |
| | | | | (0.182) | (0.153) | (0.207) |
| [Islamophobic X Terror attack], t-3 | | | | -0.027 | -0.108 | -0.306 |
| | | | | (0.129) | (0.136) | (0.127) |
| Sample size | 2152 | 2152 | 2152 | 2128 | 2128 | 2128 |
| Crime group fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Week fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Crime group x Year fixed effects | No | Yes | No | No | Yes | No |
| Crime group x Quarter fixed effects | No | No | Yes | No | No | Yes |

Note: The sample covers 538 weeks between April 2008 and August 2018 and is pooled across the four crime types (Islamophobic, Disabled, Antisemitic, Sexual orientation). The coefficients reported are for the interaction of the terror attack dummy variable and the attack identifier (the difference-in-differences estimator). Standard errors are clustered at the crime type-year level.

## Table 3: Hate Crimes and Jihadi Terror Attacks, Issues of Recording

| | Log (Hate Crimes) | | | | | |
|---|---|---|---|---|---|---|
| | All | | Victim Reported | | 999 Calls | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| [Islamophobic x Terror attack], t+3 | | 0.281 | | 0.233 | | 0.096 |
| | | (0.154) | | (0.167) | | (0.186) |
| [Islamophobic x Terror attack], t+2 | | 0.385 | | 0.170 | | 0.451 |
| | | (0.155) | | (0.303) | | (0.211) |
| [Islamophobic x Terror attack], t+1 | | 0.630 | | 0.407 | | 0.364 |
| | | (0.100) | | (0.141) | | (0.121) |
| [Islamophobic x Terror attack] | 0.836 | 0.851 | 0.799 | 0.808 | 0.638 | 0.643 |
| | (0.316) | (0.314) | (0.297) | (0.300) | (0.265) | (0.259) |
| [Islamophobic x Terror attack], t-1 | | -0.238 | | -0.128 | | 0.015 |
| | | (0.141) | | (0.148) | | (0.164) |
| [Islamophobic x Terror attack], t-2 | | 0.017 | | -0.064 | | -0.150 |
| | | (0.153) | | (0.146) | | (0.127) |
| [Islamophobic x Terror attack], t-3 | | -0.108 | | 0.041 | | 0.017 |
| | | (0.136) | | (0.139) | | (0.199) |
| Sample size | 2152 | 2128 | 2152 | 2128 | 2152 | 2128 |
| Crime group fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Week fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Crime group x Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

Note: As for Table 2.

**Table 4: Robustness - 2008-2016 and Time-Varying Effects of Recent Attacks (Manchester and London Bridge)**

| | Log (Hate Crimes) | | | |
|---|---|---|---|---|
| | Sample To End 2016 | | Heterogeneity | |
| | (1) | (2) | (3) | (4) |
| [Islamophobic x Terror attack], t+3 | | 0.144 | | 0.136 |
| | | (0.212) | | (0.162) |
| [Islamophobic x Recent terror attack], t+3 | | | | 0.613 |
| | | | | (0.167) |
| [Islamophobic x Terror attack], t+2 | | 0.312 | | 0.242 |
| | | (0.272) | | (0.213) |
| [Islamophobic x Recent terror attack], t+2 | | | | 0.349 |
| | | | | (0.217) |
| [Islamophobic x Terror attack], t+1 | | 0.646 | | 0.503 |
| | | (0.174) | | (0.183) |
| [Islamophobic x Recent terror attack], t+1 | | | | 0.375 |
| | | | | (0.223) |
| [Islamophobic x Terror attack] | 0.689 | 0.740 | 0.617 | 0.657 |
| | (0.393) | (0.404) | (0.336) | (0.346) |
| [Islamophobic x Recent terror attack] | | | 1.100 | 0.430 |
| | | | (0.367) | (0.364) |
| [Islamophobic x Terror attack], t-1 | | -0.246 | | -0.279 |
| | | (0.167) | | (0.152) |
| [Islamophobic x Recent terror attack], t-1 | | | | 0.803 |
| | | | | (0.364) |
| [Islamophobic x Terror attack], t-2 | | 0.210 | | 0.190 |
| | | (0.087) | | (0.079) |
| [Islamophobic x Recent terror attack], t-2 | | | | -1.645 |
| | | | | (0.202) |
| [Islamophobic x Terror attack], t-3 | | -0.094 | | -0.119 |
| | | (0.190) | | (0.165) |
| [Islamophobic x Recent terror attack], t-3 | | | | 0.771 |
| | | | | (0.211) |
| Sample size | 1820 | 1808 | 2152 | 2128 |
| Crime group fixed effects | Yes | Yes | Yes | Yes |
| Week fixed effects | Yes | Yes | Yes | Yes |
| Crime group x Year fixed effects | Yes | Yes | Yes | Yes |

Note: As for Table 2, except that the columns (1) and (2) specifications are for the 452 weeks between April 2008 and December 2016.

## Table 5: Anti-Muslim Hate Crimes and Newspaper Articles on Jihadi Terror Attacks

| | Log (Hate Crimes) | | | |
|---|---|---|---|---|
| | Media measure: Log(Number of articles) | | Media Measure: Peak articles, 95th percentile | |
| | (1) | (2) | (3) | (4) |
| [Islamophobic x Media measure], t+3 | | -0.008<br>(0.062) | | 0.124<br>(0.163) |
| [Islamophobic x Media measure], t+2 | | 0.092<br>(0.077) | | 0.163<br>(0.117) |
| [Islamophobic x Media measure], t+1 | | 0.131<br>(0.061) | | 0.352<br>(0.195) |
| [Islamophobic x Media measure] | 0.243<br>(0.069) | 0.246<br>(0.059) | 0.755<br>(0.179) | 0.760<br>(0.185) |
| [Islamophobic x Media measure], t-1 | | -0.184<br>(0.061) | | -0.255<br>(0.122) |
| [Islamophobic x Media measure], t-2 | | -0.009<br>(0.047) | | -0.051<br>(0.100) |
| [Islamophobic x Media measure], t-3 | | 0.008<br>(0.067) | | -0.151<br>(0.071) |
| Sample size | 2152 | 2128 | 2152 | 2128 |
| Crime group fixed effects | Yes | Yes | Yes | Yes |
| Week fixed effects | Yes | Yes | Yes | Yes |
| Crime group x Year fixed effects | Yes | Yes | Yes | Yes |

Note: As for Table 2. Peak Articles is a dummy equal to one when the number of articles is in the top 5 percent of the distribution.

**Table 6: Granger Causality Tests Based Upon Daily Time Series of Islamophobic Hate Crime and Number of Articles Published in UK Newspapers**

| | Granger causality tests, p-values | |
|---|---|---|
| | (1) | (2) |
| Terror attack | Media → Islamophobic hate crime | Islamophobic hate crime → Media |
| Lee Rigby | 0.000 | 0.761 |
| Charlie Hebdo | 0.009 | 0.285 |
| Tunisia | 0.014 | 0.985 |
| Paris November | 0.000 | 0.829 |
| Brussels | 0.027 | 0.592 |
| Nice | 0.446 | 0.218 |
| Berlin | 0.378 | 0.190 |
| London Westminster | 0.524 | 0.506 |
| Manchester | 0.004 | 0.134 |
| London Bridge | 0.006 | 0.333 |

Note: P-values of the Wald statistic testing the null hypothesis that the coefficients on all the lags of the endogenous variable are jointly zero are reported. The sample for each is the time period 30 days before and 30 days after the day of the relevant terrorist attacks.

**Table 7: Comparison of Perpetrators of Islamophobic Hate Crimes With Perpetrators of Other Hate Crimes and All Crimes**

| | Perpetrators of Islamophobic Hate Crime | Perpetrators of Non-Islamophobic Hate Crime | Perpetrators of All Crime (Excluding Islamophobic Hate Crime) | Hate Crime Gap | Crime Gap |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) – (2) | (1) – (3) |
| Male | 0.81 | 0.76 | 0.83 | 0.05** | -0.01 |
| Age | 30.86 | 28.79 | 28.41 | 2.07*** | 2.45*** |
| White | 0.91 | 0.87 | 0.86 | 0.04** | 0.06*** |
| Asian | 0.04 | 0.07 | 0.07 | -0.03** | -0.03** |
| Arab | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| Black | 0.04 | 0.05 | 0.07 | -0.01 | -0.03** |
| Number of offenders | 1.43 | 1.34 | 1.31 | 0.08* | 0.12** |
| Distance to crime (km) | 2.56 | 2.24 | 2.64 | 0.32* | 0.08 |
| Sample size[a] | 473 | 11992 | 604642 | | |

Note: ***, ** and * respectively denote significance at the 1, 5 and 10 percent levels. a denotes that sample size is a maximum of 473 perpetrators of Islamophobic hate crime, 11992 perpetrators of non-Islamophobic hate crime and 60462 perpetrators of all crime and summary statistics may vary depending on the missing values.

## Appendix

## Selected Examples of Media Reporting

THE Sun JUST 40p

Monday, November 23, 2015 BRITAIN'S BEST-SELLING PAPER thesun.co.uk

2 FOR 1 WINTER DAYS OUT VOUCHER INSIDE: PAGE 28

Vic's a big soap star

I'M A CELEBRITY Get Me Out Of Here!

SEE PAGE 9

EXCLUSIVE: SHOCK POLL

Claims .. the prince

**Charles: Climate change link to IS**

By EMILY ANDREWS

PRINCE Charles has blamed the rise of IS and the migrant crisis on climate change.

The heir to the throne claimed on Sky News that there were strong links between a lack of action on green issues, refugees and terrorism.

He said climate change had made "a huge impact" on the spread of conflict and terror across the globe.

And it was one of the "major reasons" for the conflict between rebels, IS and Syrian President Bashar al-Assad.

The prince, 67, said of the migrant crisis: "One

*Continued on Page Six*

EXCLUSIVE

Vardy's family rift over fiancée

PAGES 16 & 17

# 1 in 5 Brit Muslims' sympathy for jihadis

**'WAKE-UP CALL' AFTER PARIS BLITZ**

By TOM NEWTON DUNN

Political Editor

NEARLY one in five British Muslims has some sympathy with those who have fled the UK to fight for IS in Syria.

The number among young Muslims aged 18-34 is even higher at one in four.

The figures emerged in our exclusive poll conducted after the Paris atrocities led by French and Belgian jihadis returning from the war zone.

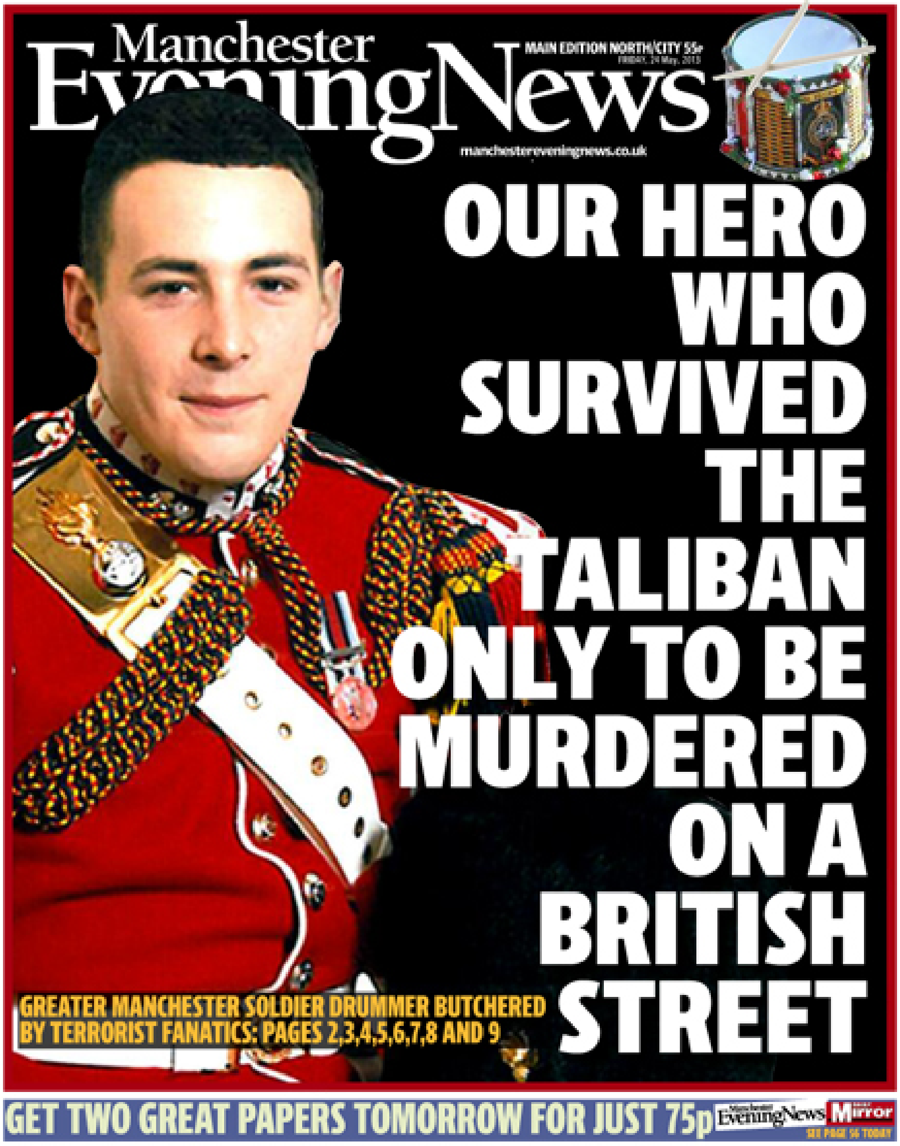
Prominent Muslims said the poll was a wake-up call.

Labour London Mayor hopeful Sadiq Khan tells The Sun

*Continued on Page Five*

KELVIN MacKENZIE: 'TIME FOR BRITAIN TO SHUT DOOR' PAGE 13

Support .. Brit Jihadi John who went to Syria



Manchester Evening News

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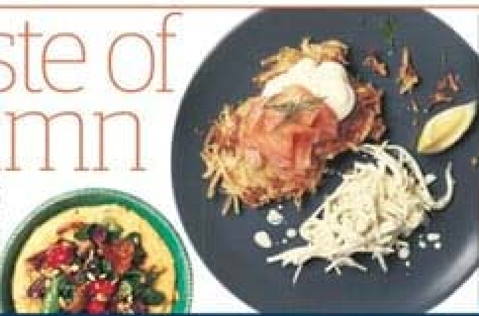

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**Toby Jones, Britain's busiest and best actor**

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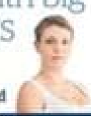
## Life with big breasts



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