Are the effects of terrorism short-lived?

Supplementary Information (SI) Appendix

For Online Publication

Contents

A Further Insights

A.1 Terrorism, risk perceptions and emotions

In this section, we offer theoretical insights on two intertwined issues. First, to motivate the choice of the variables of interest that we label 'first-order effects' (that is, risk perceptions and emotional reactions), we elaborate on their relation and how they shape policy preferences. Second, we discuss whether there are *ex ante* expectations with regards to the duration of these (first order) effects.[1]

Risk perceptions and emotions as first-order effects

In the article, we explore whether audiences perceive high risks of future terrorist attacks and heightened emotions of a negative valence in the aftermath of an attack. We consider risk perceptions and the negative emotions stimulated by terrorism as 'first-order effects' and highly consequential variables given their downstream effects on cognition, policy preferences and well-being (see, e.g., Epifanio, 2016; Sønderskov et al., 2021; Bove et al., 2021; Helbling and Meierrieks, 2022).

To elaborate, the 'first-order' effects of terrorist attacks on emotions and cognition are mechanisms through which the changes in political attitudes associated with terrorism are realised (Lambert et al., 2010; Huddy et al., 2005, 2009; Skitka et al., 2006). For instance, Huddy et al. (2005) find that anger in the wake of terrorist acts is linked with increased support for domestic and international anti-terrorism efforts. Huddy et al. (2009) find that feelings of insecurity and perceptions of threat influence support for aggressive anti-terrorism measures, including the curtailment of domestic civil liberties, tougher visa checks, and support for the war in Afghanistan. Leading explanations of the 'rally round the flag' effect suggest that this is the result of emotions of a negative valence (Lambert et al., 2010).

Two different strands of the psychology literature underpin the discussions of the linkages between emotions, risk perceptions, and policy attitudes. Intergroup emotion theory (IET), in particular, theorises that emotions condition inter-group dynamics, and conceptualises anger as a state in which some members of a social group are able to attribute blame to an out-group agent or entity. Consequently, IET suggests that high levels of

[1] In Appendix E, we also provide a theoretical formulation that can help the interpretation of our findings.

anger in a population may lead to policy preferences for aggressive military action which seek to retaliate against an identifiable target. Small et al. (2006) find that respondents who identified themselves as 'angry' when asked to write about the 9/11 terrorist attacks were likely to make various causal and attributional claims about the attack.

On the other hand, terror-management-theory (TMT) suggests that 'mortality salience', or the continuing cognition of the inevitability of death, primed by traumatic events such as terrorist attacks, lead to 'ideological intensification' wherein audiences entrench their commitment to pre-existing cultural worldviews (Huddy and Feldman, 2011). This suggests an attitudinal response to terrorist attacks wherein pre-existing partisan leanings are intensified. Pyszczynski et al. (2006), for instance, find increased support for aggressive military action and support for the USA PATRIOT Act among conservative experimental subjects after 'mortality salience' interventions were made. The 'ideological intensification effect' has also been connected to prejudicial attitudes towards out-groups, or members of different ideological or cultural communities: Das et al. (2009) find that exposing subjects to news about terrorist incidents confronts them with thoughts about death, which in turn cause an increased prevalence of prejudiced attitudes towards out-groups. In light of the discussion above, and given the relation between emotions, attitudes and policies (Epifanio, 2016; Bove et al., 2021; Helbling and Meierrieks, 2022), negative emotional arousal should be considered as an important policy-relevant variable.

The effects of terrorism: intensity and duration

The psychology literature suggests that the impact of terrorist acts on emotions and risk perceptions should track each other, both in terms of intensity and duration. On one hand, this is due to the 'affect heuristic' which suggests that risk perceptions are influenced by our emotional state and are heightened by affective images and thoughts, particularly those that induce fear (Slovic et al., 2007, p.1345). The 'risk-as-feelings' model (Loewenstein et al., 2001) suggests that risk perceptions are the result of emotive assessments rather than reflecting an objective calculus of probabilities. Appraisal-tendency theory similarly holds that emotions elicit cognitive appraisals, which in turn can shape cognitions such as threat perceptions (Maguen et al., 2008). In this framework, different emotional reactions are viewed as activating different schemas which assess causation and the controllability of events. The aforementioned theories are in line with a broader view that subjective risk assessments are not informed by calculations of statistical probability (Fischhoff et al., 2005; Baucum et al., 2021).

In terms of duration though, we can isolate two contrasting *ex ante* predictions. Much of the extant literature argues that both the emotional reactions and their cognitive effects should be *short-lived*, on the basis that these are governed by a general tendency to subside quickly as individuals habituate and return to homeostasis or baseline arousal over time (Maguen et al., 2008). This suggests that terrorism elicits emotional reactions and risk assessments which parallel those caused by traumatic events more broadly; e.g., the trauma experienced by soldiers in a war (see Knudsen et al., 2005; Sniderman et al., 2019). If this thesis is correct, then we can predict – based on findings in the psychology literature and clinical guidelines for PTSD treatment – that risk perceptions and emotions should return to baseline levels between 4 to 6 weeks after a traumatic incident (Brewin, 2001; Rauch et al., 2022). This hypothesis seems to underwrite the expectations of a number of analyses (see, for instance, Giani et al., 2021), according to which the perturbation due to terrorist attacks should fade quickly and subside completely within a month. This leads to the the expectation that both the emotional and risk-assessment impacts of terrorism will subside *within 4-6 weeks*, in line with the effects of other traumatic events.

That said, several (mostly theoretical) contributions suggest – contrary to the 'return to homeostasis' hypothesis – that the emotional and risk-assessment impacts of terrorism should have a much longer duration, with observable effects lasting several months. There are two reasons raised in the literature as to why this might be the case.

First, terrorism is a trauma experienced by communities rather than individuals, causing a process of 'communal bereavment' (Schlenger et al., 2002). This predicts a different temporal duration of effects than in the case of individual traumas. Pennebaker and Harber (1993) map community traumas as following a predictable temporal pattern, starting with an initial 'emergency stage' of intense emotional reaction and intensive social manifestation that lasts for one month. This is then followed by a 'plateau' period of one month, wherein mental rumination is maintained at high levels, while the social sharing of emotion diminishes progressively. After two months, an 'adaptation stage' appears, wherein both mental rumination and outwards expressions of emotions decline. Rimé et al. (2010, p.40) explain this temporal pattern as a consequence of the collective character of shared traumas within communities. The social sharing of emotions initially causes higher event-related mental rumination, as the discourse heightens and sustains the emotional arousal directly caused by a traumatic episode. Subsequently, however, the social sharing of emotions begins to entail collective benefits, as discourse strengthens social bonds and interpersonal relationships.[2]

Second, it is theorised that the intentional nature of terrorism distinguishes it from other forms of trauma. Bux and Coyne (2009) argue that the uniquely unpredictable nature of terrorist attacks has the effect of extending the duration of heightened risk perceptions in comparison to other traumatic episodes, although they do not provide a framework for predicting the precise duration of effects. Bux and Coyne (2009)'s argument is in line with findings in the psychology literature suggesting that the severity and duration of effects caused by traumatic events with a human perpetrator are of a larger-scale compared to those caused by technological or natural disasters (Wittchen et al., 2009; Pozza et al., 2019).

This literature does not point to an exact duration of effects that we should expect in the case of terrorist attacks. Nevertheless, it suggests that terrorist incidents should cause emotional and risk-assessment effects with a significantly longer duration than those of other classes of traumatic events. The above discussion leads to a rather contrasting expectation that emotional and risk-assessment impacts of terrorism will subside *during the 3rd month after the attack* (in line with, e.g., Pennebaker and Harper's, 1993, model).

[2] Lin et al. (2017, p.2) argue that, because of such interpersonal factors, the temporal dynamics of reactions to terrorism are difficult to study in an experimental setting.

A.2 Background material on the three attacks

We focus on three deadly national terrorist incidents that occurred over the period for which we have CMS data available: the 2005 London bombings, the 2007 Glasgow airport attack and the 2013 Lee Rigby murder.[3]

On the 7th July 2005, Hassib Hussain, Mohammad Sidique Khan, Germaine Lindays, and Shezad Tanweer detonated four explosive devices in the London underground stations Aldgate, Edgware Road and Russell Square, and a double-decker bus in Tavistock Square. A total of 52 people were killed and over 700 were injured – not including the four suicide bombers who were killed instantly upon detonating their explosive-filled rucksacks. Three of the four men left Leeds in a rented car in the early morning of that day and travelled to Luton where they met the fourth perpetrator. They then travelled by train to King's Cross Station where they split up and travelled to each of the aforementioned locations. The underground bombs were detonated at 08:50. The fourth bomber failed to do so because the Norther Line was close and instead got on a bus and triggered the device at 09:47. This was the largest terrorist incident that had occurred in Great Britain since the Second World War.[4] Poignantly, this attack marked the day in which Al-Qaeda linked terrorism came to the shores of Britain. It was the first attack of its kind in the UK after 9/11 in the USA and the 2004 Madrid train bombings.

The second attack occurred at the Glasgow airport on the 30th June 2007. At 15:11 two men drove at the glass doors of the Glasgow airport terminal in a car filled with propane canisters. The vehicle was set ablaze, and upon leaving the vehicle, the driver poured petrol around and on himself, suffering severe burns. Five members of the public were injured in their attempts to help the police detain the perpetrators, but none sustained serious injuries. The attackers were identified as Bilal Abdullah, a British Muslim doctor of Iraqi ancestry, and Kafeel or Khalid Ahmed, an Indian engineer. Ahmed was the severely injured driver, who died as result of his burns on 2 August. Immediately after the attack, the police evacuated the airport and all remaining flights for the day were suspended. The attack is historically significant for Scotland, as it was the first terrorist incident to have occurred in the devolved nation since the Lockerbie bombing in 1988.

The third attack happened on the 22nd May 2013 at 14:20. Off-duty Fusilier Lee Rigby

[3]The only other deadly attack that occurred over the period 2004-2014 was the murder of Mohammed Saleem (29 April 2013). We do not consider this attack since it was motivated by right-wing extremism and it took place 23 days before the murder of Lee Rigby, and thus the individuals interviewed between the two attacks are already defined as 'control'.

[4]https://tinyurl.com/2p9hdpr7

of the Royal Regiment of Fusiliers was ran down with a car and subsequently stabbed and hacked to death with knives and a cleave in Woolwich, Southeast London. The perpetrators were Michael Adebolajo and Michael Adebowale. The men did not flee the scene and remained next to the victim's body until the police arrived nine minutes after a witness called the emergency services. The attackers were filmed telling passers-by that they had killed a soldier as revenge for the killing of Muslims by the British Army abroad. The assailants charged at the police when these arrived and, as a result, were shot. Both survived their injuries and were later found guilty of murder. Both attackers were British-born citizens of Nigerian descent who had converted to Islam. During the sentencing, Mr Justice Sweeney stated that their extremist views constituted a "betrayal of Islam". In response to this Adebowale shouted that "[t]hat [was] a lie" and Adebolajo shouted "Allahu Akbar" (Allah is the greatest).

A.3 Terrorism and emotions: evidence from tweets

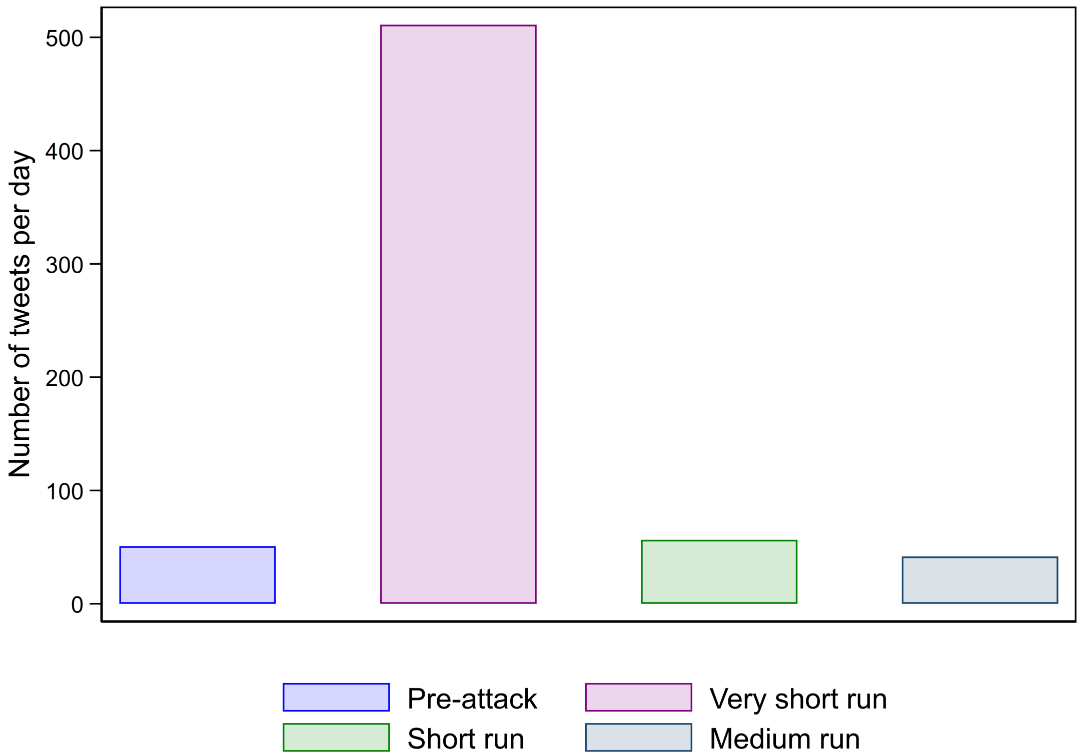
To lend further empirical support to our main findings, we use Twitter data and analyse the emotional content of terrorism-related tweets. We use Twitter's API V2 to obtain English language tweets with a geotag in the UK around the 2013 Lee Rigby murder.[5] We focus on this particular attack since Twitter was not available during the London bombings in 2005 and had a very low user count during the Glasgow airport attack in 2007. We sample the tweets that were posted within 30 days before the attack and within 120 days after the attack, and which contain the term 'terror' or other related terms, as identified using a Word2Vec algorithm. We then apply a dictionary method, NRCLex – which is based on the NRC Emotion Lexicon (Mohammad and Turney, 2013) – to assign each word an emotional affect: anger, anticipation, disgust, fear, joy, negative, positive, sadness, surprise and trust. A drawback of this analysis if that it may also capture some positive emotions about the victims of terrorist attacks or the government's response to terrorism.

Figure A.3a shows the daily average number of terrorism-related tweets across the four time frames we use in our main analysis: (i) the *pre-attack period* (30 days before the attack); (ii) the *very short run* (one week after the attack); (iii) the *short run* (the first month minus the first week after the attack); and (iv) the *medium run* (the first four months minus the first month after the attack). As can be seen quite clearly, the daily number of terrorism-related tweets went drastically up 7 days after the attack, suggesting a large interest in this event. This also indicates that this particular incident was correctly perceived by the general public as an act of terrorism. Figure A.3b compares the pre- and post-attack average values of emotions about terrorism. These are calculated using the (within-time-frame) average share of words assigned to a given emotion across all lexicon-identified words included in the terrorism-related tweets. According to this figure, there is a notable growth in the negative sentiment about terrorism in the very short run, with anger being the emotion that displays the largest increase (by about 65%) compared to the pre-attack period. This is consistent with our survey-based results where anger prevails over the other negative feelings in the very short run. As opposed to our main analysis, however, the effects appear to be shorter-lived. This is not surprising given that the Twitter textual data (based on users' own language) capture real-time emotional reactions to events, and are thus less effective at identifying the duration of these reactions – especially given how

[5]Geotagged tweets have the advantage that they provide precise information about the location from where the tweet was sent, which allows us to exclude tweets from non-UK-based users who were not exposed to the attack. However, a large proportion of UK-origin tweets are not geotagged, which reduces significantly the number of tweets we can use for this analysis.

quickly the overall public mood in social media changes and adjusts to new information and events (Lansdall-Welfare et al., 2016).

Figure A.3a: 2013 Lee Rigby murder: number of terrorism-related tweets



Notes: The figure shows the average number of terrorism-related tweets per day during the pre-attack time frame and the three post-attack time frames.

Figure A.3b: 2013 Lee Rigby murder:
sentiment analysis of terrorism-related tweets

Notes: The figure shows the share of emotions in terrorism-related tweets during the pre-attack time frame and the three post-attack time frames.

A.4 Media coverage of terrorism

In this section, we first discuss a key factor that can explain differences in the temporal dynamics of risk perceptions and emotions following terrorist attacks: the extent of media coverage. We then provide some evidence about the media cycle of three sampled attacks.

Media attention and the severity of terrorist attacks

A number of accounts argue that the temporal course of emotional reactions and risk perceptions among the public are determined by the extent of media coverage. This is connected to the concept of the 'availability heuristic' from the psychology literature which suggests that the ease of recall and imaginability of an event influences risk perceptions and the extent to which it continues to evoke affective reactions (Slovic et al., 2007, p.1345). For instance, Lichtenstein et al. (1978) use the 'availability heuristic' to explain why judged frequencies of highly publicized causes of death (e.g., accidents, homicides, fires, tornadoes, and cancer) are overestimated, while under-publicized causes (e.g., diabetes, stroke, asthma, and tuberculosis) are underestimated. Continuing coverage of terrorist acts engenders strong emotional reactions in the public, which can play a role in sustaining emotional arousal (Lerner et al., 2003) – as evidenced in both experimental settings (e.g., Lerner et al., 2003) and survey results (Tucker, 2003; Cho et al., 2003). This leads to the expectation that continuing *media coverage sustains the duration* of heightened risk perceptions and emotional reactions.

The severity of a particular attack, as measured for example by the number of victims, is also expected to increase the duration of effects. As Brandon and Silke (2006, p.177) argue, "severe events provoke a stronger initial response and slower return to baseline in the absence of further stimulation". Ganzel et al. (2007) find evidence of this thesis in an experimental setting, where they show that the intensity of traumatic events alters the speed of recovery. Overall, we should expect that terrorist attacks *with more victims* will cause more intense and long-lasting emotional and risk-perception effects.

Note that media coverage often serves as a useful proxy for the event's importance, given that the media tend to pay more attention to lethal attacks and those considered a threat to the general population. For instance, Jin et al. (2022) show that the media are much more responsive to deadly attacks and those motivated by Islamic extremism, the latter being generally perceived as posing a more systematic threat to national security and democratic values. At the same time, and as the discussion above suggests, continuing media coverage is theorised to sustain the duration of effects, but may not always reflect the intensity of the initial trauma. This is because other idiosyncratic characteristics – such as the type of victims, the perpetrator motivations and the attack method – can also influence how long a terrorist event appears in the media. As such, one can treat the coverage of an attack as a reflection of multiple factors that can lead to heightened risk perceptions and negative emotions and influence the duration of the resulting effects.

The media cycle of the three attacks

To provide some evidence about the coverage of the three sampled attacks by the national media, we analyse data on newspaper reporting from LexisNexis: an online service that searches through the text of thousands of news publications.[6] To locate relevant articles, we limit the search results to national newspapers from UK-based sources published within 30 days before each attack and within 120 days after each attack, and which include the terms 'terrorism', 'terror' or 'terrorist', and attack-specific keywords including the location of the incident.

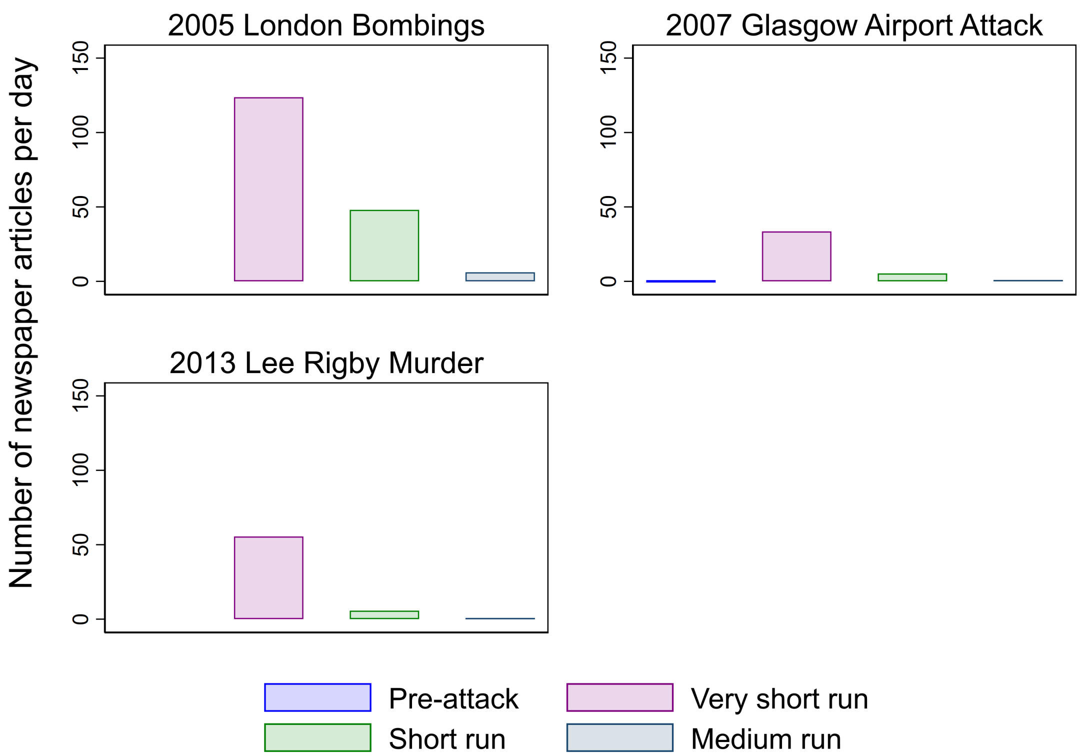
Figure A.4b shows the daily average number of LexisNexis hits (relevant articles) across the four time frames we use in our main analysis: the *pre-attack period*, the *very short run*, the *short run*, and the *medium run*. Two regularities stand out. First, the initial spike in coverage for the 2005 London bombings (in the very short run) is more than double that for the other two attacks. Second, for the 2005 London bombings, the descent from the initial peak is quite slow and coverage persists for several weeks after the attack (48 hits per day in the short run and 6 hits per day in the medium run). In contrast, for the other two attacks, the coverage quickly dissipates to zero, with 5-6 hits per day in the short run and less than 1 hit per day in the medium run. Overall, the media cycle of the three events is consistent with the temporal dynamics of risk perceptions and emotions following the attacks; i.e., the effects of the 2005 London bombings are stronger and temporally more persistent, whereas those of the other two attacks start at a lower point and display a more rapid decline.

[6]Figure A.4a presents examples of newspaper front pages published on the day after each attack.

Figure A.4a: Newspaper front pages

Notes: Selected front pages of newspapers published the day after each attack occurred. Row 1 relates to the 2005 London bombings; row 2 to the 2007 Glasgow airport attack; and row 3 to the 2013 Lee Rigby murder.

Figure A.4b: Newspaper coverage by attack



Notes: The figure shows the average number of LexisNexis hits per day during the pre-attack time frame and the three post-attack time frames.

B Additional Empirical Analyses

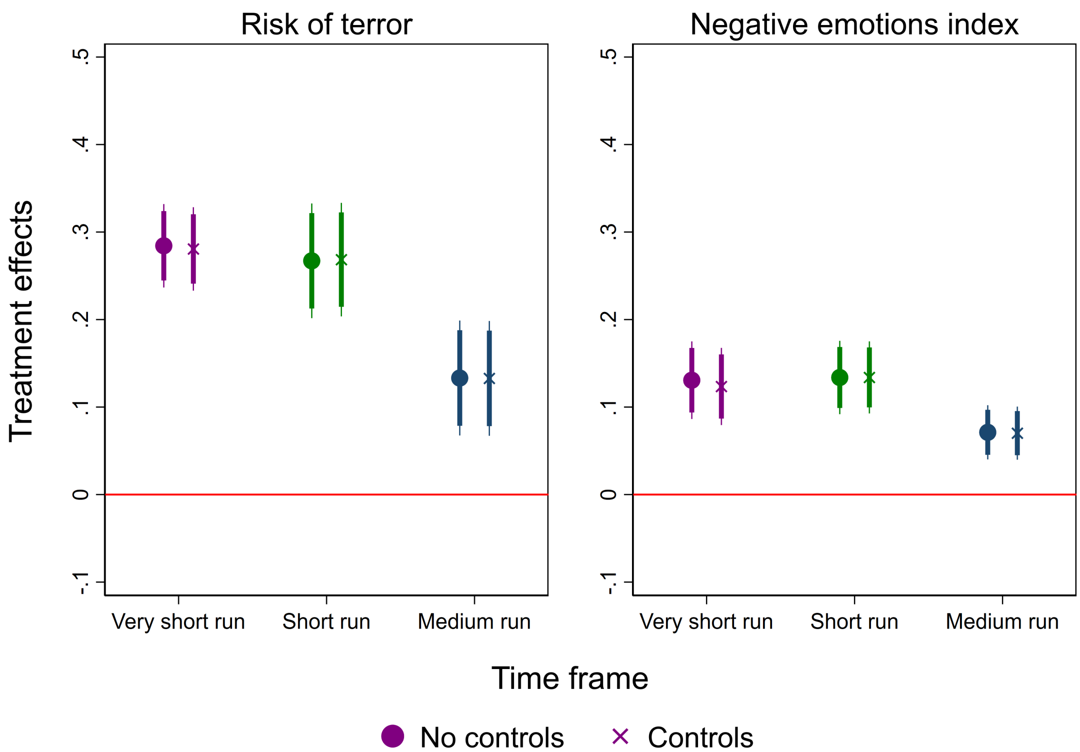
B.1 Covariates and imbalances

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. To ensure that our results are not affected by such imbalances, we report estimates both before and after augmenting the baseline model with the following individual-level controls: gender (dummy: female vs male), age, age squared, ethnicity (dummy: white vs non-white), family status (dummy: has children vs does not have children), education (dummy variables capturing six education groups), and income (dummy variables capturing nine income groups). As shown in B.1a, controlling for all these variables has no impact on our estimates, despite the fact that the sample sizes are now much smaller – see also Tables D.1 and D.2 in Appendix D for the full regression results.

As a further step, we perform balancing tests in the aforementioned characteristics across treatment and control units. Tables B.1a, B.1b and B.1c report the corresponding results for each time frame (very short run, short run and medium run, respectively). We can see that, when we exploit information from the short and medium runs, there is a strong balance across treated and control units for nearly all attributes. On the other hand, when we exploit information from the very short run, we can observe some significant differences in a number of attributes (age, age squared, gender and the last education group), which is not surprising given the smaller number the treated units in this case.

To correct for the imbalances reported above, we re-weight the sample through entropy balancing (Hainmueller, 2012) such that the distribution of covariates among control units matches the moment conditions (until skewness) of the treated units. As shown in Figure B.1b, this exercise produces similar results as in Figure B.1a and does not change our inferences. As an alternative approach, we rely on coarsened exact matching (CEM, Blackwell et al., 2009) 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 survey questions of interest. Figure B.1c shows the results when we perform CEM on the full set of characteristics (mentioned above) and restrict the matched control units to come from the same attack-by-region group as the treated units. The evidence obtained is in line with our previous findings.

Figure B.1a: Main results: with and without control variables



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Table B.1a: Covariate balanace: very short run

	Pre-attack		Post-attack			
	Mean	Std. dev.	Mean	Std. dev.	Diff.	p-value
Female	0.52	0.50	0.47	0.50	0.05	(0.01)
Age	49.07	14.91	54.36	13.93	-5.30	(0.00)
Age squared	2629.80	1477.75	3149.24	1491.80	-519.45	(0.00)
Has children	0.40	0.49	0.38	0.48	0.02	(0.29)
Education: 14 or under	0.01	0.11	0.01	0.10	0.00	(0.53)
Education: 15	0.13	0.33	0.11	0.31	0.02	(0.13)
Education: 16	0.22	0.42	0.22	0.42	0.00	(0.87)
Education: 17-18	0.21	0.41	0.20	0.40	0.01	(0.53)
Education: 19-20	0.08	0.27	0.07	0.26	0.01	(0.54)
Education: 21 or over	0.35	0.48	0.38	0.49	-0.04	(0.03)
White	0.96	0.19	0.95	0.23	0.01	(0.08)
Income: Less than or £5,000	0.04	0.19	0.03	0.17	0.01	(0.29)
Income: £5,000 to £9,999	0.08	0.27	0.07	0.26	0.01	(0.48)
Income: £10,000 to £1,4999	0.12	0.32	0.11	0.32	0.00	(0.90)
Income: £15,000 to £1,9999	0.13	0.33	0.14	0.34	-0.01	(0.48)
Income: £20,000 to £2,4999	0.12	0.33	0.11	0.32	0.01	(0.44)
Income: £25,000 to £2,9999	0.11	0.32	0.12	0.33	-0.01	(0.47)
Income: £30,000 to £3,9999	0.16	0.37	0.18	0.39	-0.02	(0.14)
Income: £40,000 to £4,9999	0.11	0.32	0.12	0.32	-0.00	(0.84)
Income: £50,000 or more	0.13	0.34	0.11	0.32	0.02	(0.16)
Observations	3,253		933		4,186	

Notes: This table shows the mean of covariates across treatment and control units, together with conventional t-tests for differences in means across the two groups.

Table B.1b: Covariate balance: short run

	Pre-attack		Post-attack			
	Mean	Std. dev.	Mean	Std. dev.	Diff.	p-value
Female	0.52	0.50	0.51	0.50	0.01	(0.38)
Age	49.07	14.91	48.42	14.50	0.64	(0.08)
Age squared	2629.80	1477.75	2554.95	1414.38	74.85	(0.04)
Has children	0.40	0.49	0.40	0.49	-0.00	(0.83)
Education: 14 or under	0.01	0.11	0.02	0.13	-0.01	(0.06)
Education: 15	0.13	0.33	0.13	0.33	0.00	(0.94)
Education: 16	0.22	0.42	0.23	0.42	-0.00	(0.84)
Education: 17-18	0.21	0.41	0.20	0.40	0.01	(0.51)
Education: 19-20	0.08	0.27	0.08	0.27	-0.00	(0.83)
Education: 21 or over	0.35	0.48	0.34	0.48	0.00	(0.87)
White	0.96	0.19	0.96	0.19	-0.00	(0.51)
Income: Less than or £5,000	0.04	0.19	0.03	0.16	0.01	(0.06)
Income: £5,000 to £9,999	0.08	0.27	0.08	0.28	-0.01	(0.46)
Income: £10,000 to £14,999	0.12	0.32	0.12	0.33	-0.00	(0.61)
Income: £15,000 to £19,999	0.13	0.33	0.12	0.33	0.00	(0.90)
Income: £20,000 to £24,999	0.12	0.33	0.13	0.34	-0.01	(0.39)
Income: £25,000 to £29,999	0.11	0.32	0.11	0.32	0.00	(0.88)
Income: £30,000 to £39,999	0.16	0.37	0.16	0.37	-0.00	(0.83)
Income: £40,000 to £49,999	0.11	0.32	0.11	0.31	0.01	(0.46)
Income: £50,000 or more	0.13	0.34	0.13	0.34	0.00	(0.82)
Observations	3,253		3,144		6,397	

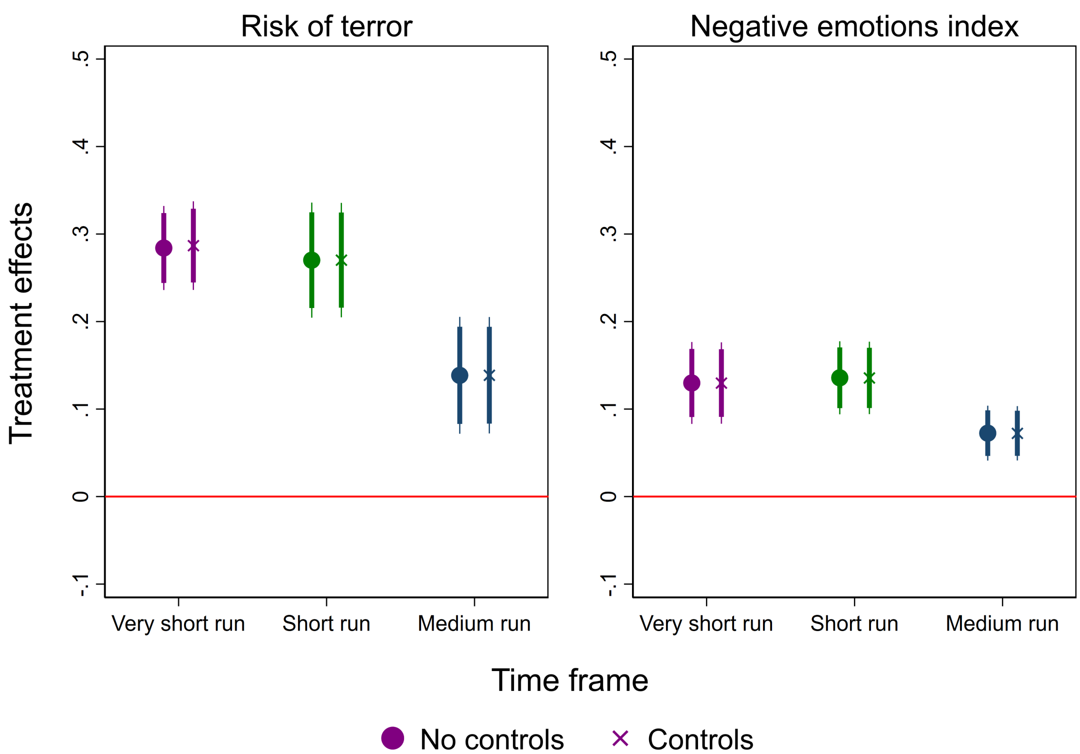
Notes: This table shows the mean of covariates across treatment and control units, together with conventional t-tests for differences in means across the two groups.

Table B.1c: Covariate balance: medium run

	Pre-attack		Post-attack			
	Mean	Std. dev.	Mean	Std. dev.	Diff.	p-value
Female	0.52	0.50	0.51	0.50	0.00	(0.64)
Age	49.07	14.91	48.50	14.62	0.57	(0.06)
Age squared	2629.80	1477.75	2566.04	1428.36	63.75	(0.03)
Has children	0.40	0.49	0.40	0.49	-0.01	(0.53)
Education: 14 or under	0.01	0.11	0.02	0.12	-0.00	(0.12)
Education: 15	0.13	0.33	0.13	0.34	-0.00	(0.49)
Education: 16	0.22	0.42	0.23	0.42	-0.00	(0.59)
Education: 17-18	0.21	0.41	0.21	0.41	0.00	(0.73)
Education: 19-20	0.08	0.27	0.07	0.26	0.00	(0.53)
Education: 21 or over	0.35	0.48	0.34	0.47	0.01	(0.49)
White	0.96	0.19	0.96	0.20	0.00	(0.82)
Income: Less than or £5,000	0.04	0.19	0.03	0.17	0.01	(0.03)
Income: £5,000 to £9,999	0.08	0.27	0.08	0.27	0.00	(0.71)
Income: £10,000 to £14,999	0.12	0.32	0.12	0.32	-0.00	(0.53)
Income: £15,000 to £19,999	0.13	0.33	0.12	0.32	0.01	(0.42)
Income: £20,000 to £24,999	0.12	0.33	0.12	0.33	-0.00	(0.80)
Income: £25,000 to £29,999	0.11	0.32	0.12	0.32	-0.00	(0.82)
Income: £30,000 to £39,999	0.16	0.37	0.16	0.37	-0.00	(0.57)
Income: £40,000 to £49,999	0.11	0.32	0.11	0.32	0.00	(0.97)
Income: £50,000 or more	0.13	0.34	0.14	0.35	-0.00	(0.56)
Observations	3,253		10,617		13,870	

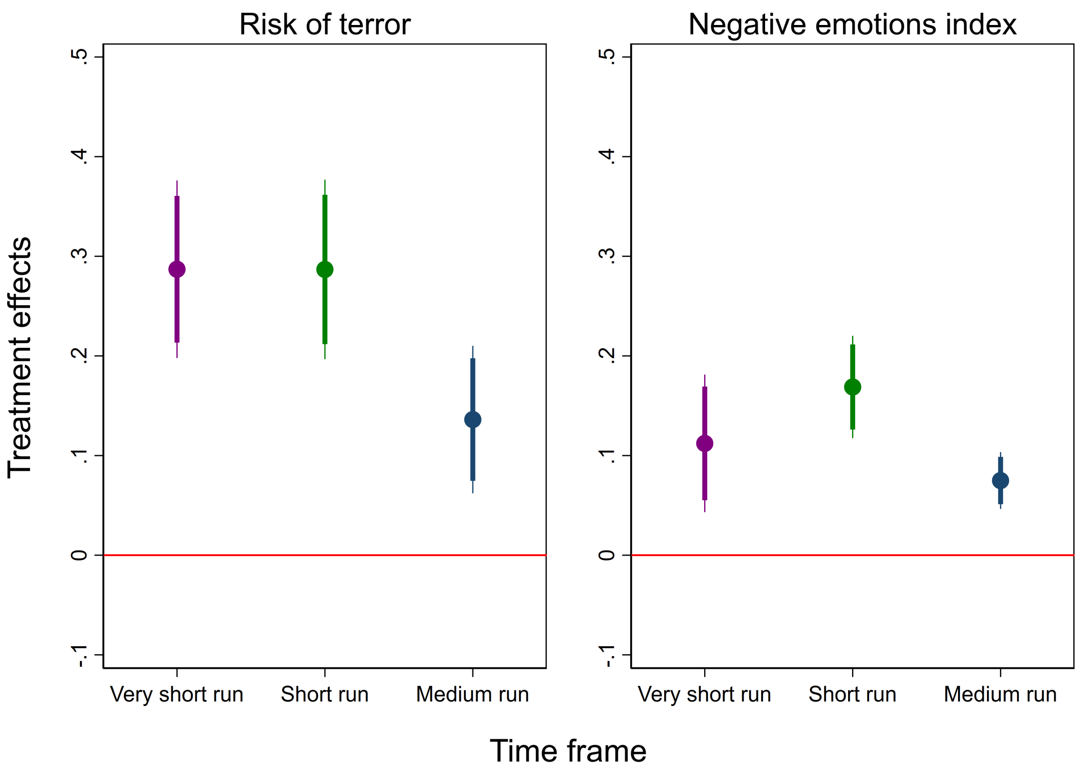
Notes: This table shows the mean of covariates across treatment and control units, together with conventional t-tests for differences in means across the two groups.

Figure B.1b: Entropy balancing



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. The estimates are balanced using entropy weights that match the mean, variance and skewness of covariates across the treatment and control units. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Figure B.1c: Coarsened-exact matching



Notes: This figure shows the treatment effects after performing coarsened-exact matching. To locate matches, we use the full set of control variables and restrict the matched control units to come from the same attack-by-region group as the treated units. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.2 Identification validity tests

To strengthen our causal inference, we need to address two additional issues. The first relates to the failed terrorist attack in July 2005; the second relates to pre-existing trends.

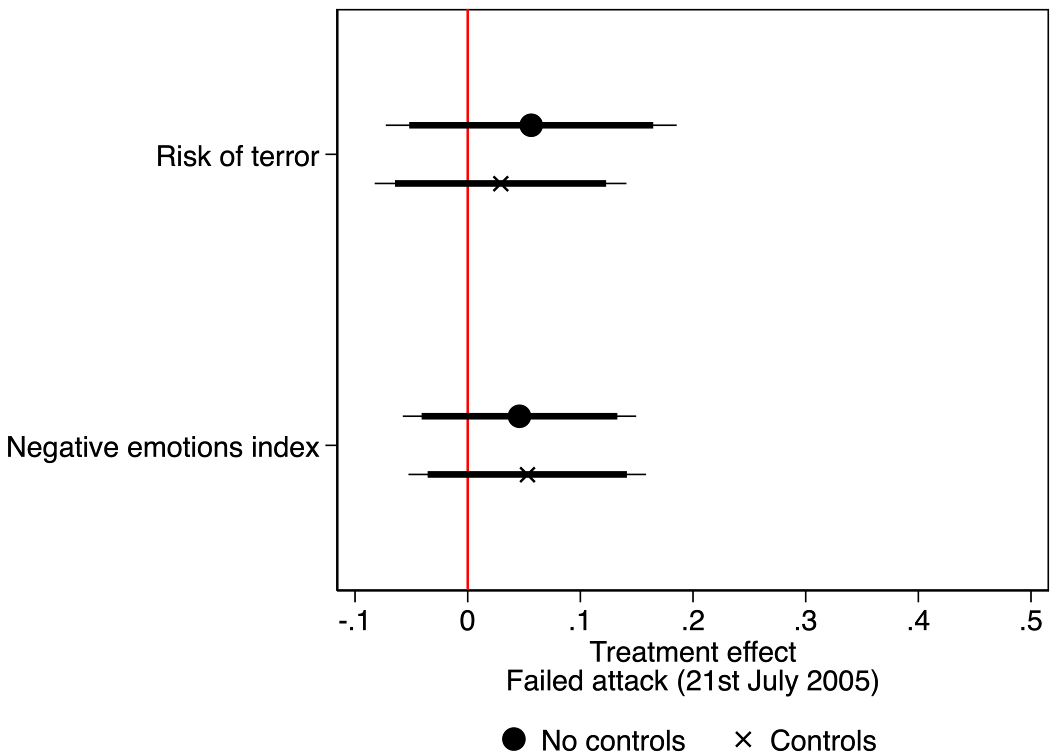
Testing for the failed attack. On the 21st of July 2005, two weeks after the 2005 London bombings, there was a failed plot in which terrorists re-targeted the London underground network. The bombs failed to explode and there were no fatalities. This 'collateral' event could jointly affect our outcome variables, and thus bias our estimates.[7] To test for this, we focus on the original treatment group of the deadly attack, and compare individuals interviewed in the week after the failed attack with those interviewed in the week before this attack. The results are reported in Figure B.2a. For both outcome variables, the 'post-failed-attack' estimate is very close to zero and fails to reach statistical significance, which indicates that this collateral event is not affecting our main effects. This is likely because the original shock was so large and persistent that there was no room for a further increase in risk perceptions and negative feelings.

Testing for pre-existing trends. It is possible that our estimates capture pre-existing time trends in the outcome variables, which are unrelated to the timing of the attacks. To address this possibility, we consider placebo treatments during the pre-attack period – as recommended by Muñoz et al. (2020) – and perform three alternative tests based on different time spans and cut-off points. First, we focus on the baseline (30-day) pre-attack sample and set the placebo attack date to be in the middle of the pre-attack period. In this way, the 'placebo control' group includes the individuals interviewed 16-30 days before the actual attacks, and the 'placebo treatment' group includes the individuals interviewed 1-15 days before the actual attacks. Second, we perform a series of placebo tests based on 30-day bandwidths; i.e., we assume that the attacks occurred on days -31, -61 and -91, and compare the responses of individuals interviewed 30 days before and 30 days after these cut-off points. Third, we employ a longer-term time span that covers 240 days prior to each attack, and split the sample of respondents in two equal-duration parts; i.e., 120 days pre-treatment (individuals interviewed 121-240 days before the attacks), and 120 days post-treatment (individuals interviewed 1-120 days before the attacks). Figures B.2b, B.2c and B.2d show the corresponding results. In most cases, the placebo treatments have zero effect on people's risk assessments and negative feelings, and whenever there is some evidence of statistically significant pre-post differences, these are very small in magnitude.

[7] As pointed out by Muñoz et al. (2020), this can be seen as a problem of an imprecise treatment, as it makes it difficult to narrowly interpret the effect as a consequence of the treatment itself.

To draw better inferences about the magnitude of the actual effects compared to longer-term pre-attack patterns, in Appendix C.1 we plot the binned scatterplots for all three attacks together, and each individual attack separately, based on a 120-day bandwidth.[8] As can be observed in these figures, the 120-day time series before the two smaller-scale attacks are relatively flat, while those before the 2005 London bombings display some declining patterns (see also discussion in Appendix C.1).

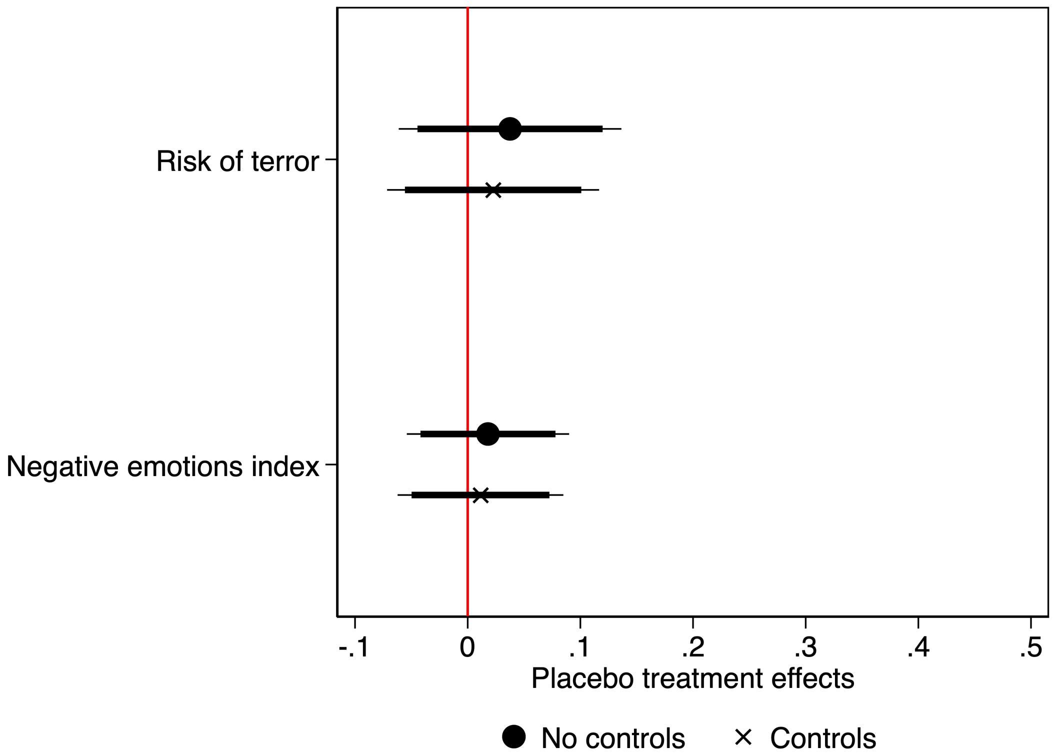
Figure B.2a: Collateral event: failed 21st July 2005 attack



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

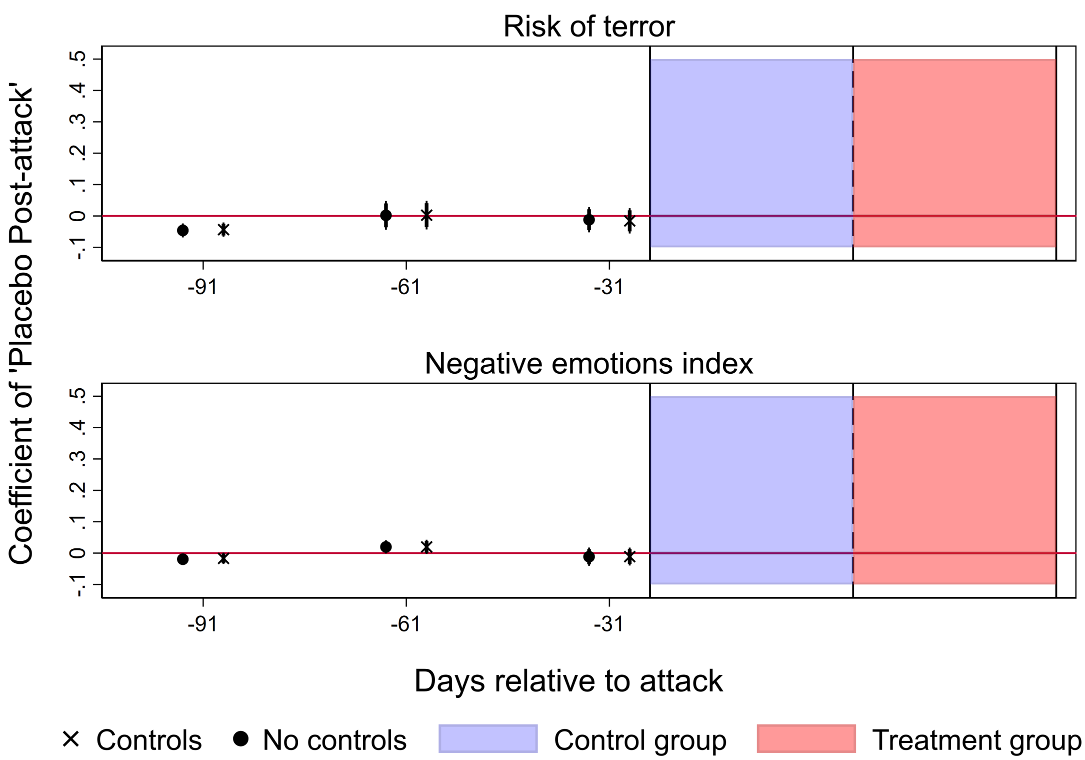
[8]As pointed out in Section 3, the binned scatterplots depict the non-parametric relationship of interest and account for the presence of outliers and distributional differences in the data over time.

Figure B.2b: Testing for pre-existing time trends:
16-30 days vs 1-15 days before attacks



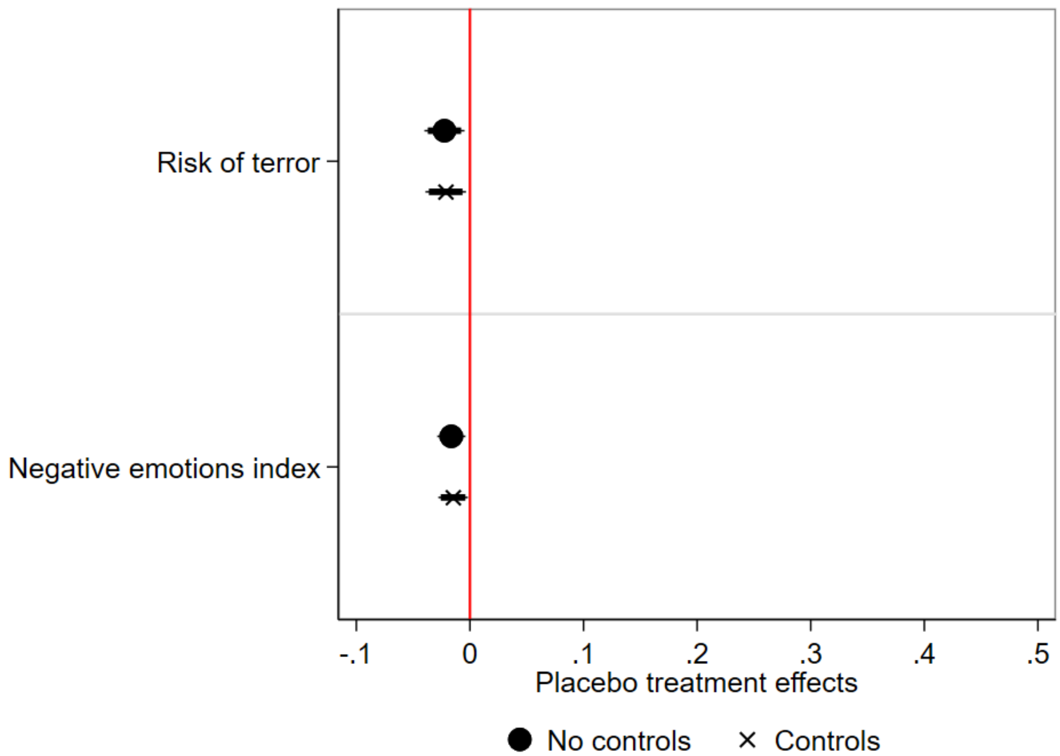
Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Figure B.2c: Testing for pre-existing time trends:
placebo attack dates based on 30-day bandwidths



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Figure B.2d: Testing for pre-existing time trends:
121-240 days vs 1-120 days before attacks



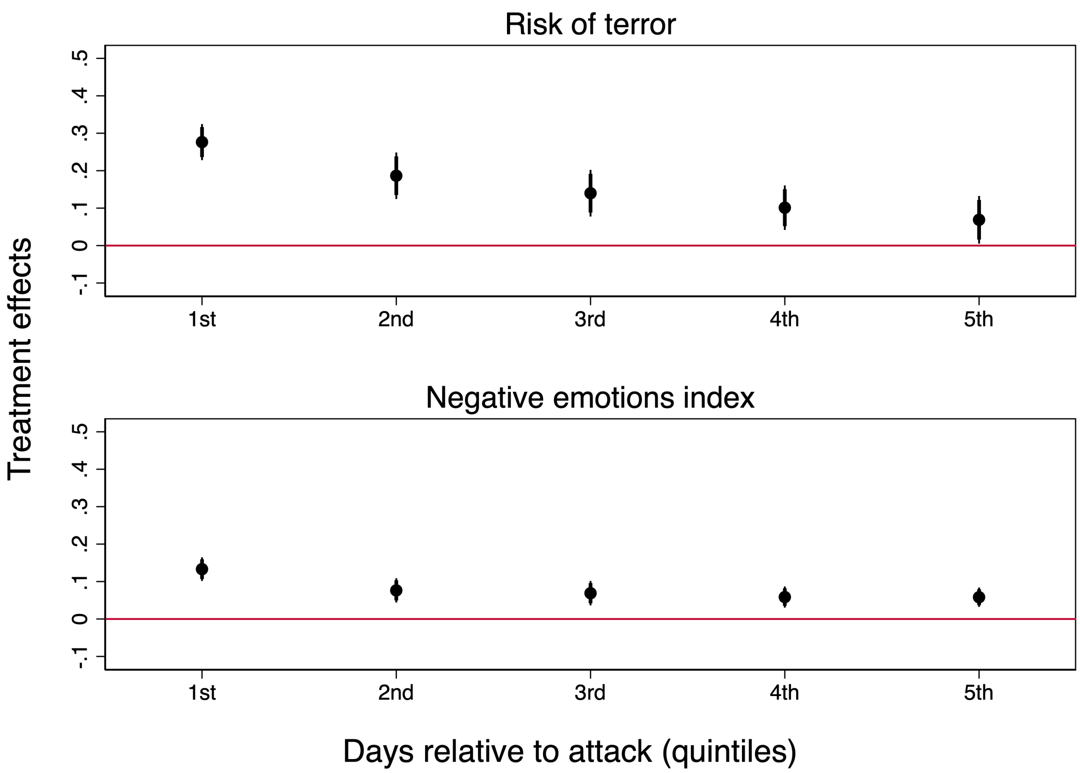
Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.3 Quintile-based time frames

In our main analysis, we explore the non-linear effect of terrorism on risk perceptions and negative emotions by dividing the post-attack period of 120 days into three distinct time intervals: the *very short run*, the *short run*, and the *medium run*. The choice of cut-off points to create these intervals is motivated by arguments and findings in the psychology literature regarding the duration of emotional reactions and risk assessments following traumatic events (see discussion in Section A.1), and is line with the framework used in Giani et al. (2021). However, as a robustness check, we run the baseline regressions using quintile-based time frames. Splitting the treatment sample into five equal frequency groups based on the moderator (in our case, the number of days since the attacks) is consistent with the recommendations of Hainmueller et al. (2019) for testing susceptibility of the results to misspecification bias (see also Falcó-Gimeno et al., 2022).

As shown in Figure B.3, using this alternative specification does not change the inferences drawn from earlier findings. Once again, we can observe a sharp increase in risk assessments and negative feelings in the short run (as now captured by the 1st quintile; i.e., 3-4 weeks after the attacks), followed by a decline in the medium run (as now captured by the 2nd-5th quintiles). Yet, even at the highest quintile of time distance, the treatment effects retain their statistical significance and are above the pre-treatment levels, which runs counters to the "return to homeostasis" hypothesis predicting a quick return to baseline levels after a short-lived and dramatic spike.

Figure B.3: Quintile-based time frames



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.4 Placebo tests: alternative outcomes

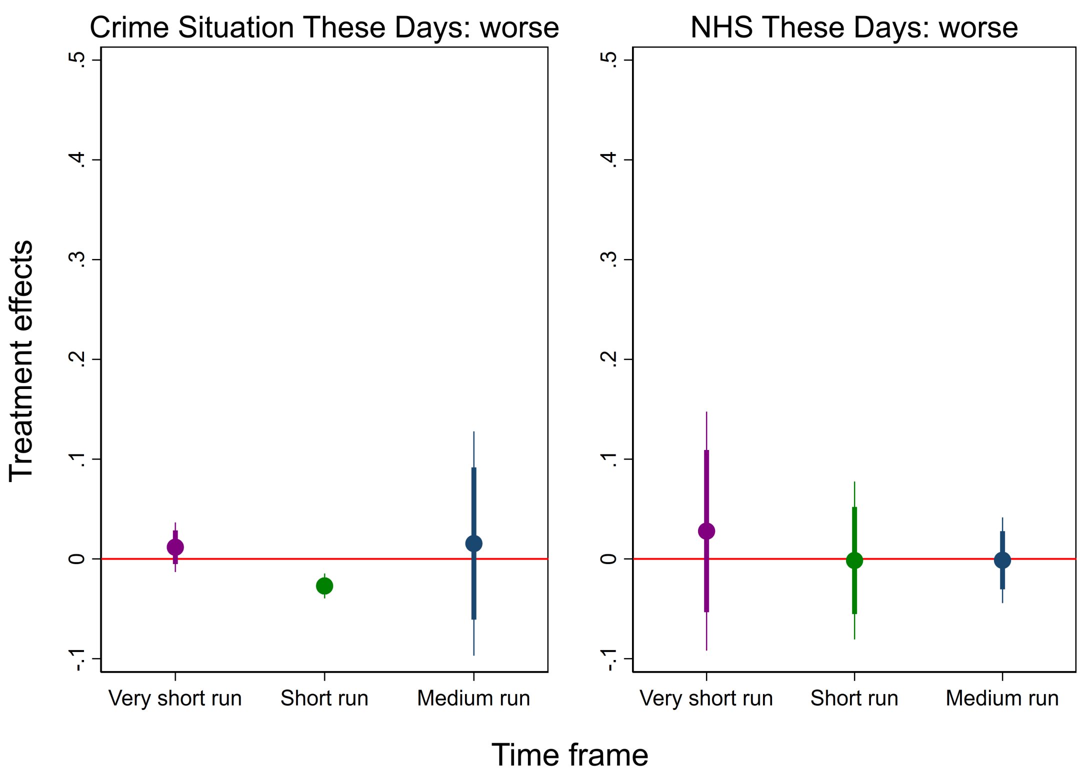
In this section, we perform placebo tests where we examine the treatment effect on outcomes that should not be affected by terrorist incidents (or, at least, in the same way).

First, we employ measures capturing public assessments about two other key issues: crime and public healthcare. To construct these measures, we consider individuals' responses to the statements *"Do you think that the crime situation in Britain these days is...*" and *"Do you think the National Health Service in Britain these days is...*", and, as in the case of terrorism risk assessments, we assign value 1 to the responses 'a little worse' and 'a lot worse' (and 0 to all the other responses). Figure B.4a shows the results for these two outcomes, based on the same regression set-up as before. The treatment estimates are very close to zero and, in most of the cases, they fail to reach statistical significance. The only exception is when we exploit information from the short run, where we can observe a very small displacement effect, suggesting that exposure to terrorism sways public opinion away from other popular issues. At the same time, the absence of positive and statistically significant effects for the crime-related outcome confirms that the terrorist incidents are correctly perceived by the large audience as acts as terrorism rather than violent crime.[9]

Second, we employ measures capturing negative emotions about the state of the economy, which is often ranked as a top national concern by the British public. As in the case of terrorism, we consider individuals' responses to the question *"Which, if any, of the following words describe your feelings about the country's general economic situation?"*, and construct dummy variables for the four negative emotions (anger, disgust, unease and fear), together with a composite index. Once again, we can see that the resulting estimates are very small in magnitude, statistically insignificant or in the opposite direction; i.e., people reporting less negative feelings about the economy in the immediate aftermath of a terrorist attack (see Figure B.4b).

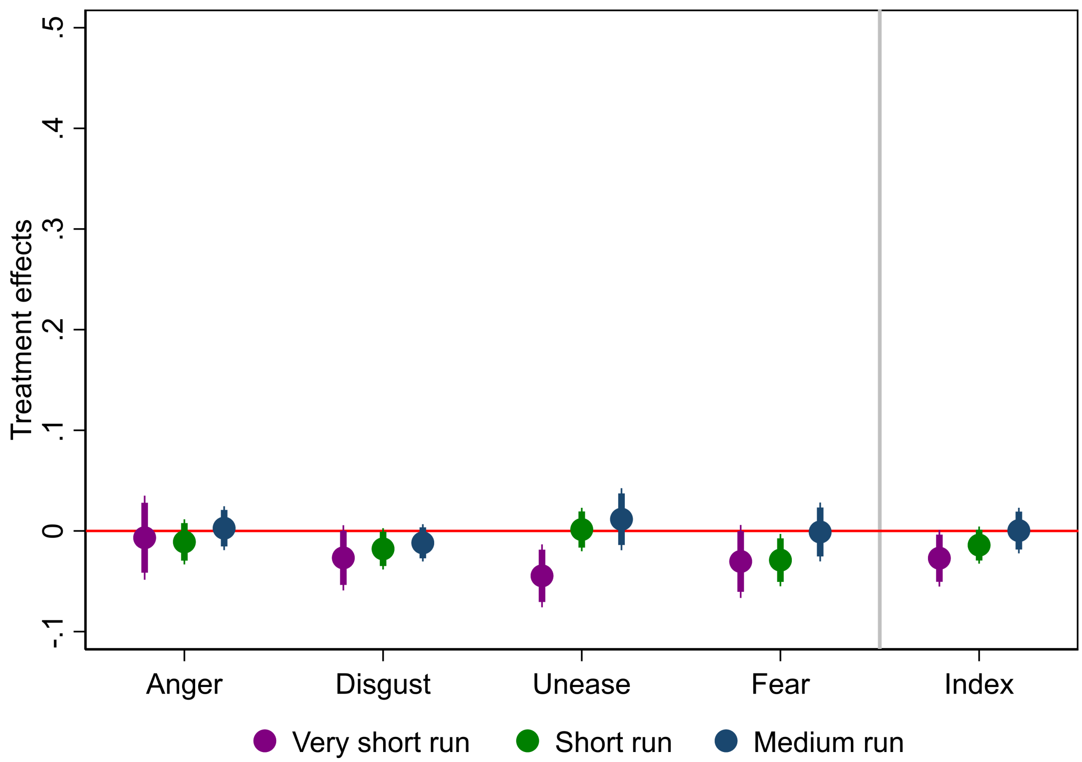
[9] See Brück and Müller (2010) on what drives concerns about terrorism vis-a-vis crime.

Figure B.4a: Public assessments about crime and public healthcare



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Figure B.4b: Negative emotions about the state of the economy

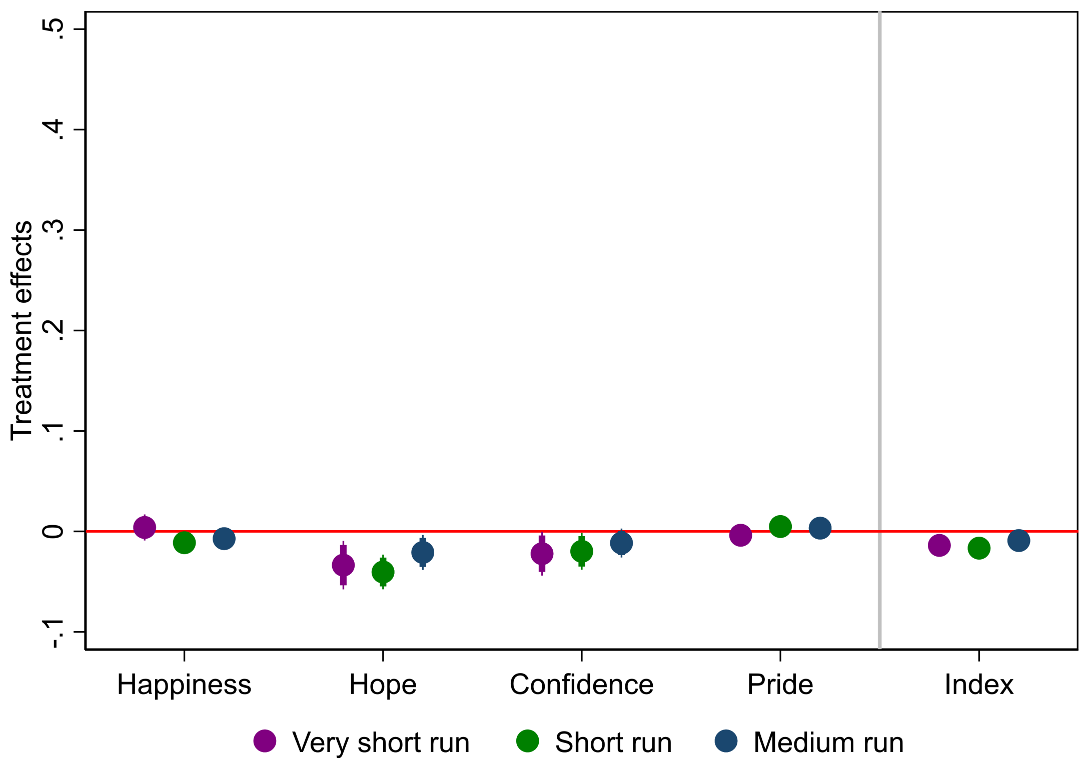


Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.5 Positive emotions about the risk of terrorism

In this section, we examine how positive emotions about the risk of terrorism evolve over time in response a terrorist attack. To do so, we run the same regressions as in Figure 3, but we now focus on the four positive emotions: happiness, hope, confidence and pride. The results are displayed in Figure B.5. Generally speaking, we observe the opposite patterns to those of negative emotions: after a terrorist attack, individuals are less likely to report positive feelings about the risk of terrorism – though the corresponding effects appear to be very small in magnitude and are mostly driven by a reduction in 'hope' and 'confidence' in the very short run and short run.

Figure B.5: Positive emotions about the risk of terrorism



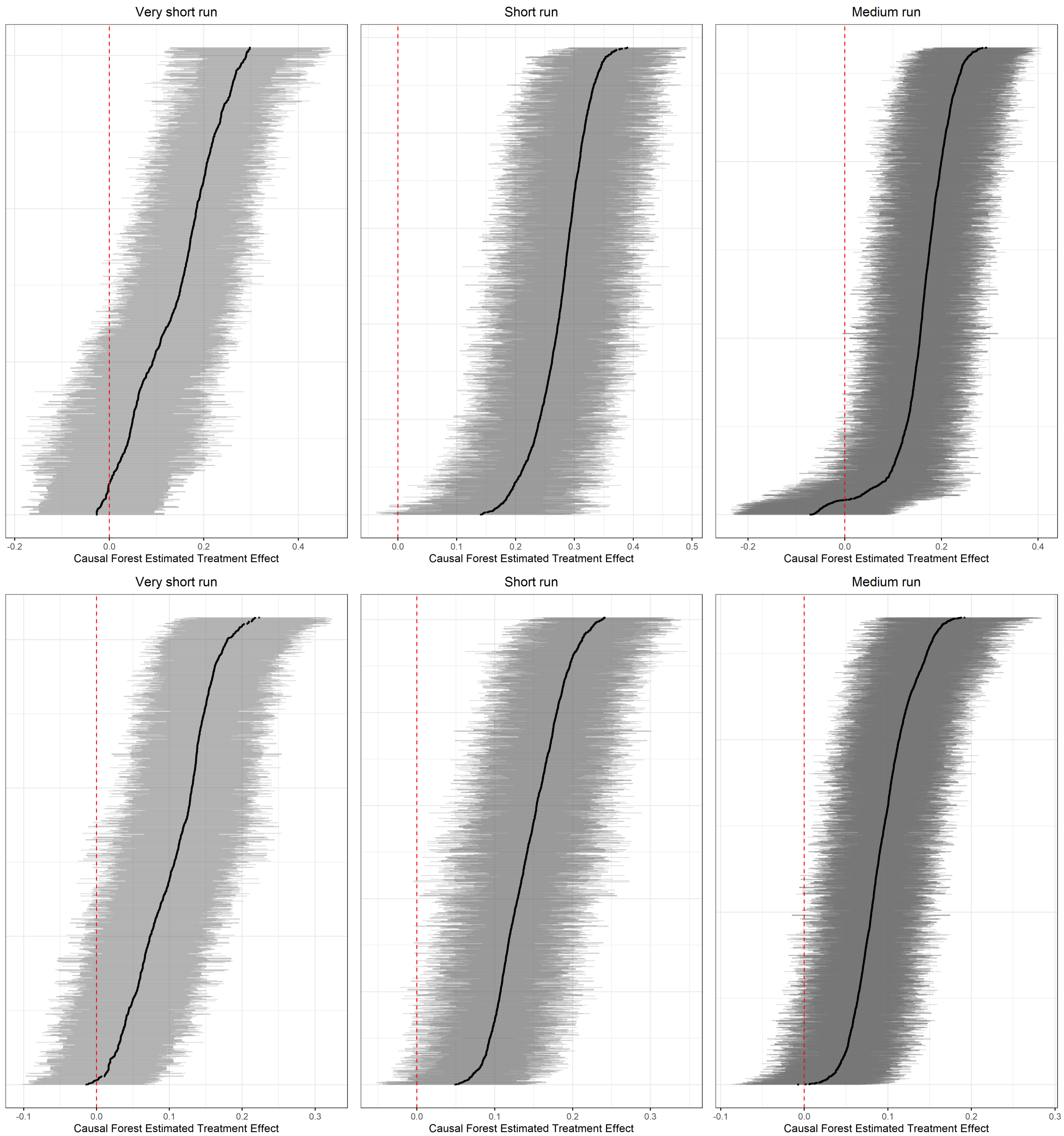
Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.6 Heterogeneous effects across individuals

We have seen, so far, that terrorism causes an increase in risk perceptions and negative emotions, which persists in the medium run. We now ask if this evidence is consistent across all population groups regardless of observed characteristics; that is, whether individuals with a certain covariate profile can exhibit the opposite patterns (e.g., report lower risk perceptions after the attacks) or be associated with shorter-lived effects. To do so, we employ a causal forest approach. Causal forest is a machine learning algorithm that automates the search for heterogeneity in the treatment effect (see Athey et al., 2019). In other words, it estimates the treatment effect for each individual in our sample as a function of their covariate profile, known as the conditional average treatment effect (CATE).

Figure B.6 plots the CATEs (ordered by effect size) across the three time frames along with the 95% confidence intervals. The first row reports the results for risk perceptions, whereas the second row reports the results for the negative emotions index. According to these plots, over 95% of individuals in our sample have a positive treatment effect. In addition, we detect that the CATE is significantly different from the local average treatment effect (LATE) only in the very short run. This indicates that there is some evidence of heterogeneous effects, with respect to individuals' characteristics, in the immediate aftermath of an attack. A visual inspection of the very short run figures informs us that the source of the heterogeneity likely stems from positive but insignificant effects rather than from negative ones. Moving beyond this time frame, we do not find evidence that the CATE is significantly different from the LATE, which indicates no heterogeneity. All in all, the analysis in this section reveals a high degree of homogeneity in the direction (and duration) of the terrorism effects across individuals.

Figure B.6: Causal forest estimates



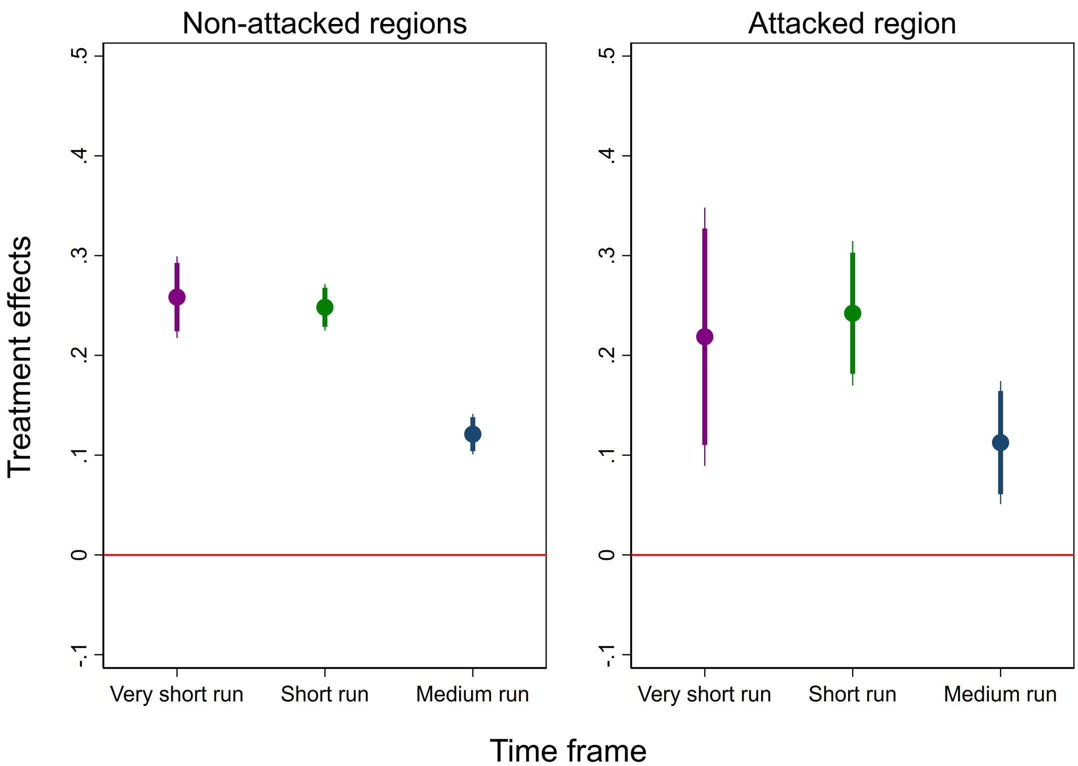
Notes: The dependent variable in row 1 is *Risk of terror*. The dependent variable in row 2 is *Negative emotions index*. Estimated effects are obtained using the grf package for R with the recommended settings of honest splitting (i.e., sub-sample splitting) and 4,000 trees. Black lines indicate estimated treatment effect for each individual, as a function of their covariate profile, ordered by effect size. Grey horizontal lines indicate 95% confidence intervals. Covariates include the full list of control variables (as reported in Section B.1) and attack-by-region fixed effects.

B.7 Attacked vs non-attacked regions

Physical proximity to a terrorist attack can amplify the perception of threat and the personal sense of vulnerability, increase mortality salience as individuals feel more connected to the environment where the attack occurred, and affect the extent to which the event is covered by the local media (Nussio et al., 2021; Bove et al., 2021, 2022). In line with these arguments, one would expect that distance from terrorism will act as a moderating factor whereby individuals that reside further away from an attack are less likely to report increased risk perceptions and negative feelings after the attacks. Yet, the existence of a "proximity effect" has become a debated issue and Agerberg and Sohlberg (2021) find that individuals close to the attack do not display stronger reactions compared to less proximate individuals.

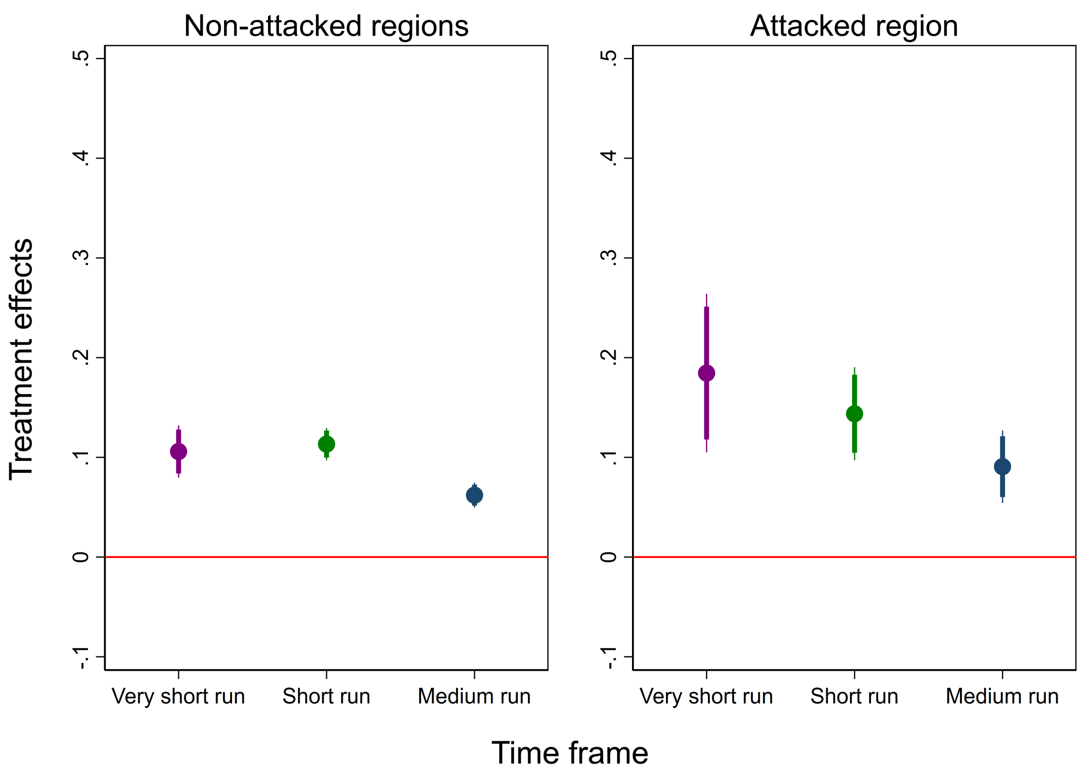
In the CMS data, the location of the respondents is only available at the region level. As such, to test whether physical proximity can influence the terrorism-induced reactions, we run the same analysis separately for individuals living in non-attacked regions and those living in attacked regions, with the latter capturing the regions in which the attacks took place. Figures B.7a and B.7b display the corresponding results for the two outcomes of interest. We can see that the effects on negative feelings are much stronger in the attacked regions than in the non-attacked regions (especially in the very short run and short run), whereas the effects on risk perceptions are quite similar between the two samples. Overall, the analysis in this section suggests that, while physical distance can play a moderating role in how individuals respond to terrorism, this role is rather weak. This is likely due to the severity and emblematic nature of the attacks in our sample – see also Pickard et al. (2023) for a similar finding.

Figure B.7a: Risk of terror: attacked vs non-attacked regions



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects (for the non-attacked regions) and attack fixed effects (for the attacked regions). Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

Figure B.7b: Negative emotions index: attacked vs non-attacked regions

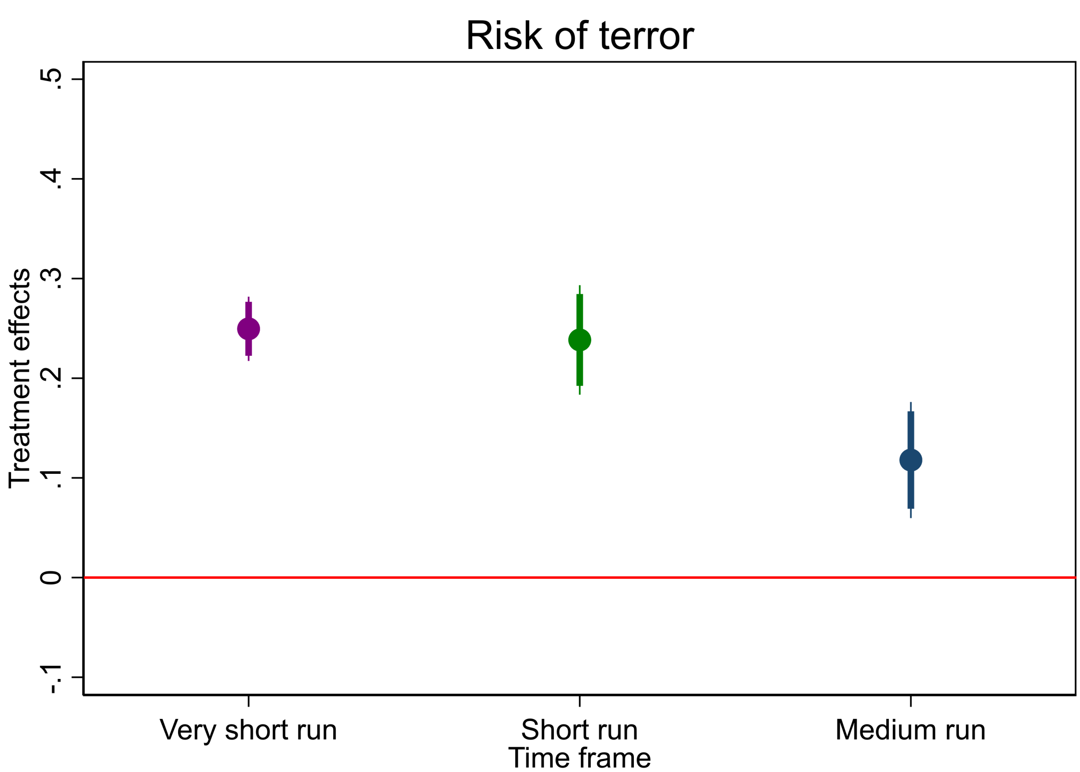


Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects (for the non-attacked regions) and attack fixed effects (for the attacked regions). Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

B.8 Alternative estimation method: probit model

Throughout our main analysis, we estimate the treatment effects on binary outcomes, like the variable for terrorism risk perceptions, using a linear probability model. As recently shown by Timoneda (2021), the linear probability model produces very accurate estimates both with highly common data and rare events data. Nevertheless, to address any remaining concerns about the accuracy of our chosen estimation technique, we check robustness to estimating our baseline specification for *Risk of terror* (Figure 2) using a probit model. As shown in Figure B.8, the choice of the estimation model does not affect our inferences.

Figure B.8: Probit estimation



Notes: The treatment effects are estimated using a probit model, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval.

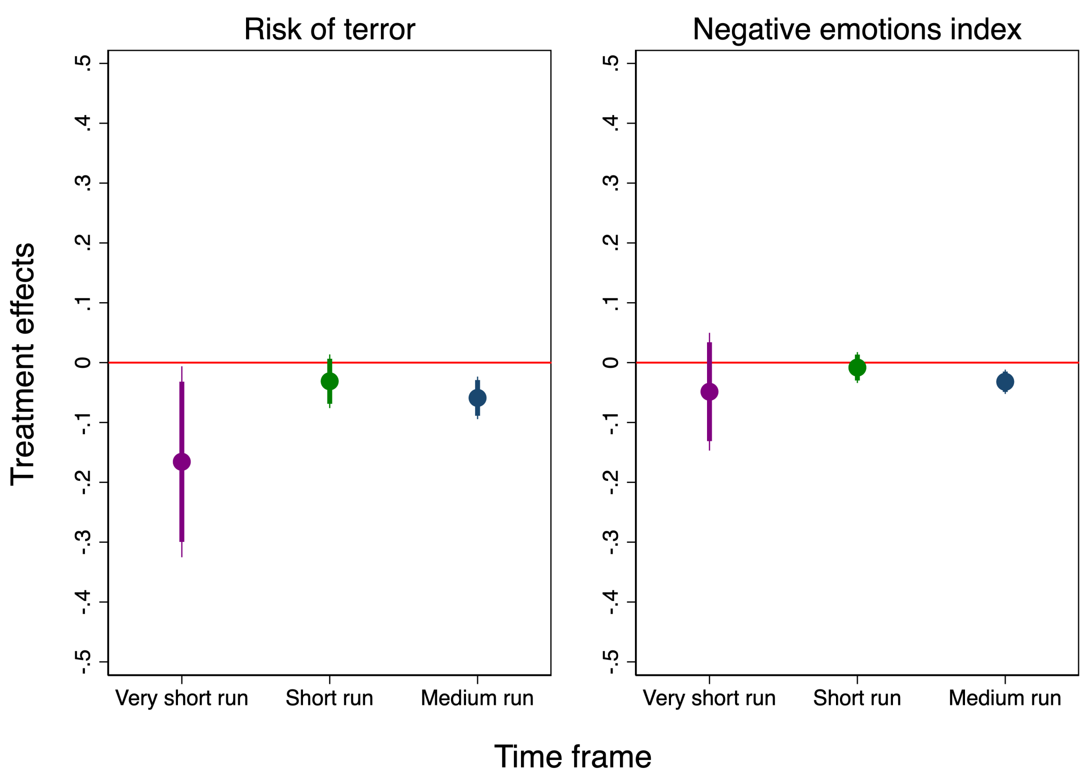
B.9 Comparison with a foiled and low-reported attack

In our main analysis, we provide evidence that foiled terrorist attempts, when they are largely reported in the media, can lead to increases in threat perceptions and negative emotions, which however are much smaller in magnitude and duration than those caused by deadly attacks. In this section, we benchmark these results against a foiled attack with minimal media coverage. To do so, we run the same regression set-up as before but we now consider individual responses around the 2012 assassination attempt of Lt-Gen Kuldeep Singh Brar,[10] which went relatively unreported in the mainstream national media. As can be seen in Figure B.9, this particular attack did not cause heightened risk perceptions and emotional reactions: the treatment effects are close to zero, statistically insignificant or in the opposite direction.[11] Comparing these estimates with those of the three foiled airplane hijackings (Figure 5), suggests that extensive media coverage can affect people's reactions to terrorism even when the incidents are classified as 'unsuccessful'.

[10]This foiled attack occurred near Oxford Street in London on the 30th September 2012, when four men attempted to murder Lt-Gen Kuldeep Singh Brar, a retired lieutenant general of the Indian army, who led 'Operation Blue Star' in 1984 to flush out pro-Khalistan militants from the Golden Temple. The suspects were arrested by counter-terrorism officers following searches at addresses in London and the Midlands. The Global Terrorism Database classifies this attack as 'unsuccessful'.

[11]Note that the tests in the very short run have low statistical power, as the post-attack sample is extremely small (30 observations only). Merging the samples in the very short-run and the short-run and running the same regression produces statistically insignificant estimates for both outcome variables.

Figure B.9: Risk of terror and negative emotions:
a foiled and low-reported attack



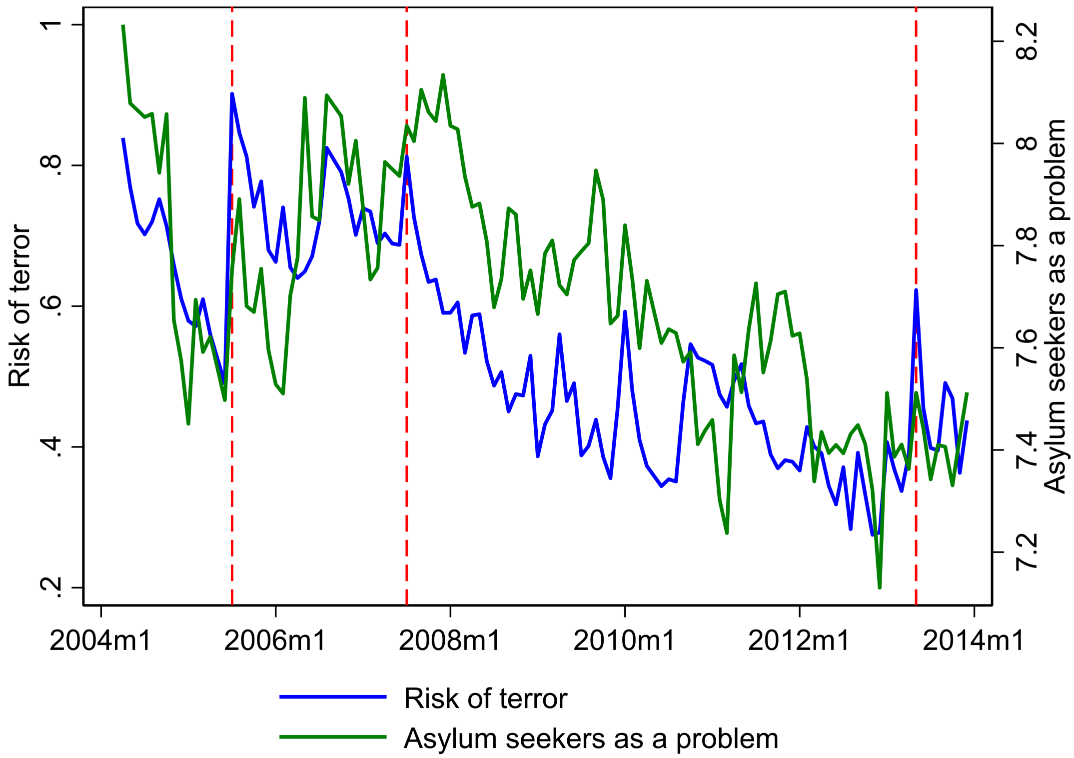
Notes: The treatment effects are estimated using OLS, controlling for region fixed effects. Standard errors are clustered at the region level. Fat (thin) lines signify the 90% (95%) confidence interval. N (very short run) = 923; N (short run) = 1,761; and N (medium run) = 4,125.

B.10 Second-order effects: migration attitudes

In this section, we take our analysis one step further and examine one of the 'second-order echo effects' of terrorism: its influence on migration attitudes. To do so, we explore individuals' answer to the question *"How important a problem is the number of asylum seekers coming to Britain these days?"*, with responses ranging on a 0-10 scale. Figure B.10a shows the evolution of the monthly average values of this variable (i.e., *Asylum seekers as problem*) over the sample period, together with the corresponding (monthly average) values of our main outcome variable, *Risk of terror*. As it stands out quite clearly, the two variables move together in the long run, which provides some evidence of a positive relationship between them. It is also particularly striking that both terrorism risk perceptions and public concerns over asylum seekers decline continuously during a period of no deadly (Islamic) national attacks; i.e., the months between the Glasgow airport attack and the Lee Rigby murder.

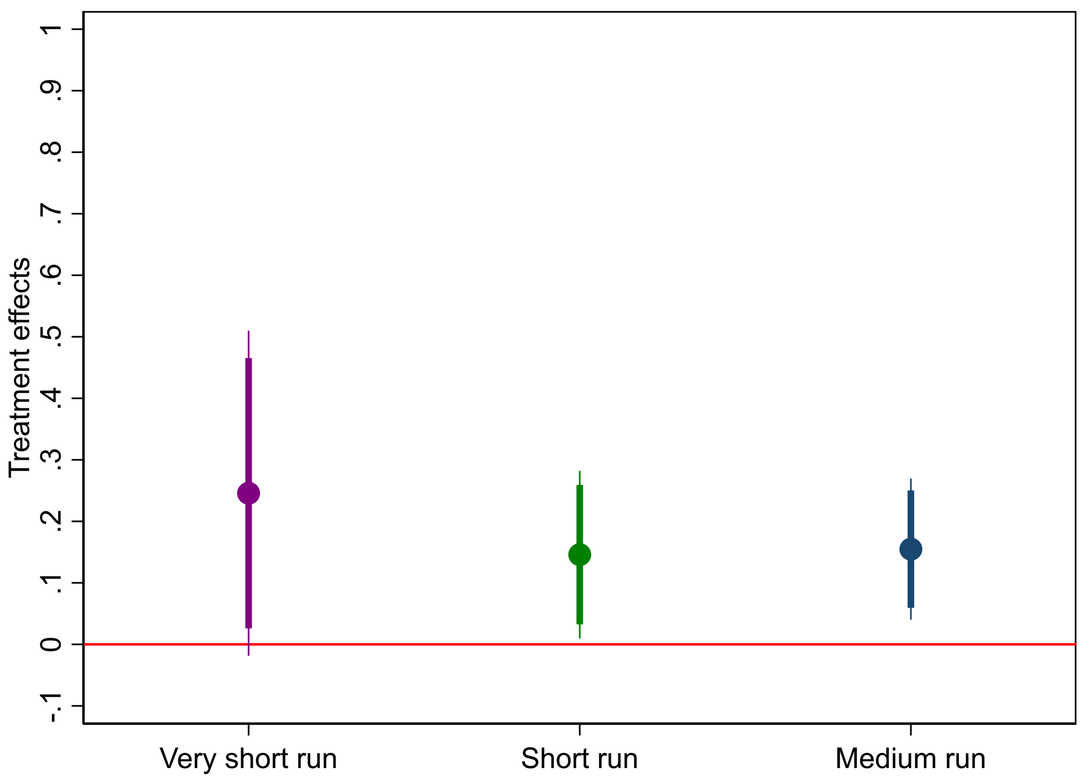
Figure B.10b presents the treatment effects when we estimate our baseline model using the variable *Asylum seekers as problem* as the outcome. We find that, in the first week after the attacks, individuals are, on average, 0.25 points higher up the scale; that is, they perceive the number of asylum-seekers as a more important problem compared to before the attacks. This is in line with previous studies documenting that, in the wake of (Islamic) terrorist attacks, members of the broader audience are more likely to perceive foreigners and out-groups in general as a threat to the homogeneity of the nation-state population (Abou-Chadi, 2016; Helbling and Kalkum, 2018; Böhmelt et al., 2020; Bove et al., 2021; Helbling and Meierrieks, 2022). However, our results also reveal that terrorism can cause a more permanent shift in such perceptions: the initial surge is followed by a slight decrease in the short run and then a stabilisation at the same levels in the medium run. That said, it must be acknowledged that the second-order terrorism effects (e.g., on attitudes not directly elicited by terrorism) are likely to be subject to bias arising from the occurrence of other unrelated events, especially when we exploit information from longer time intervals (see also discussion in Section 2).

Figure B.10a: Evolution of *Risk of terror* and *Asylum seekers as a problem* over the sample period



Notes: The red dotted lines indicate the timing of the three attacks used in the analysis: the London bombings (7 July 2005); the Glasgow airport attack (30 June 2007); and, the Lee Rigby murder (22 May 2013).

Figure B.10b: Asylum seekers as a problem



Notes: The treatment effects are estimated using OLS, controlling for attack-by-region fixed effects. Standard errors are clustered at the attack-by-region level. Fat (thin) lines signify the 90% (95%) confidence interval. N (very short run) = 4,207; N (short run) = 6,380; and N (medium run) = 13,847.

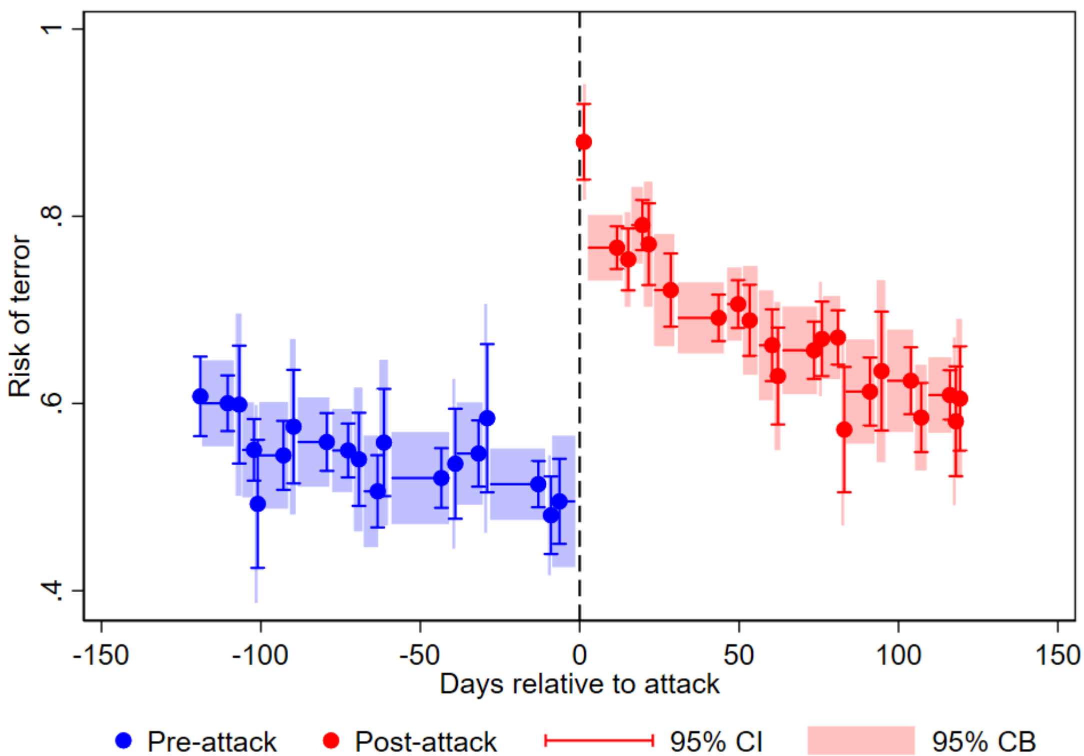
C Binned Scatterplots

C.1 Binned scatterplots based on a 120-day bandwidth

In this section, we provide sets of binned scatterplots – showing the conditional relationship between the treatment indicator and the mean of the outcome variable – based on a 120-day bandwidth; i.e., we compare responses of individuals interviewed 120 days before the attacks to those of individuals interviewed 120 days after the attacks.[12] Figure C.1a and Figure C.1e present the scatterplots for *Risk of terror* and *Negative emotions index*, respectively, when we pool data from all the attacks together; whereas Figures C.1b-C.1d and Figures C.1f-C.1h present the scatterplots for the two variables when we consider data from each of the three attacks separately. Overall, the patterns displayed in these figures support our key findings: after the 2005 London bombings, there is a level shift upwards in both risk perceptions and negative emotions that is sustained over time, whereas after the two smaller-scale terrorism incidents, there are significant changes in risk perceptions and negative emotions, which however subside within one month.

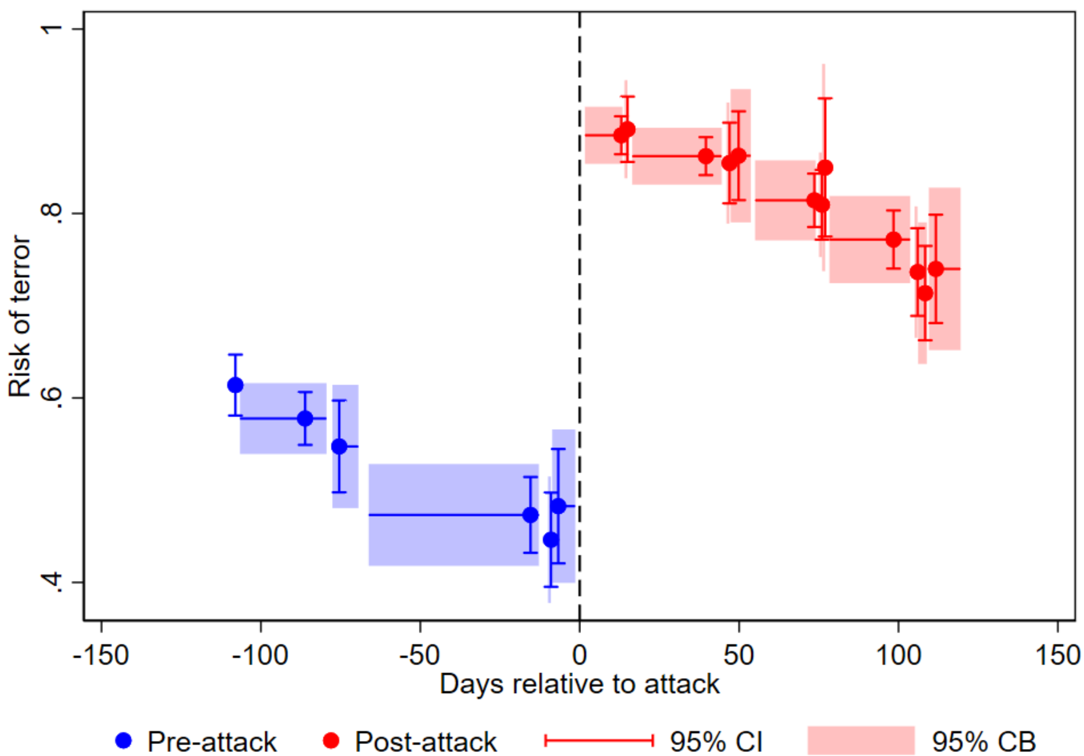
[12] One of the most important choices in constructing a binned scatterplot is the number of bins. As noted by Starr and Goldfarb (2020), more bins allow the researcher to identify more curvilinear patterns, but because each bin has fewer data points there will be more idiosyncratic variance; in contrast, fewer bins include more data points, leading to more precision, but may be less effective in identifying non-linearities. To trade off the bias and variance in an objective way, we choose the number of bins by minimizing the integrated mean squared error of the binned scatterplot, as in Cattaneo et al. (2019a).

Figure C.1a: Risk of terror: all attacks



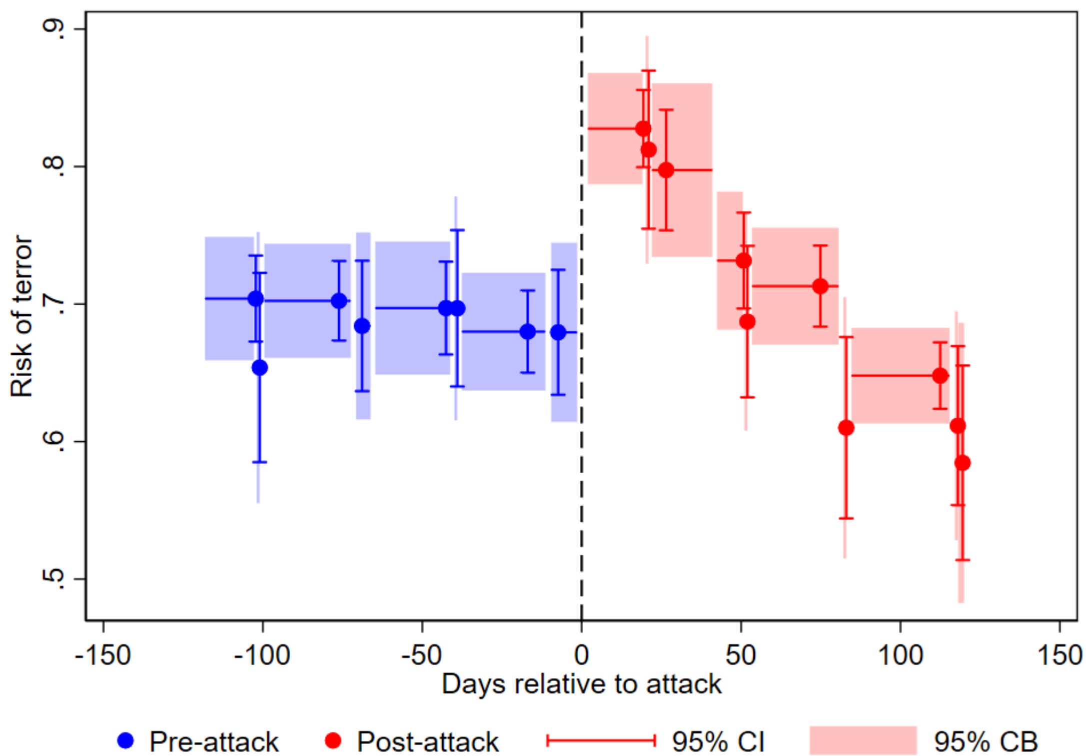
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes attack-by-region fixed effects.

Figure C.1b: Risk of terror: 2005 London bombings



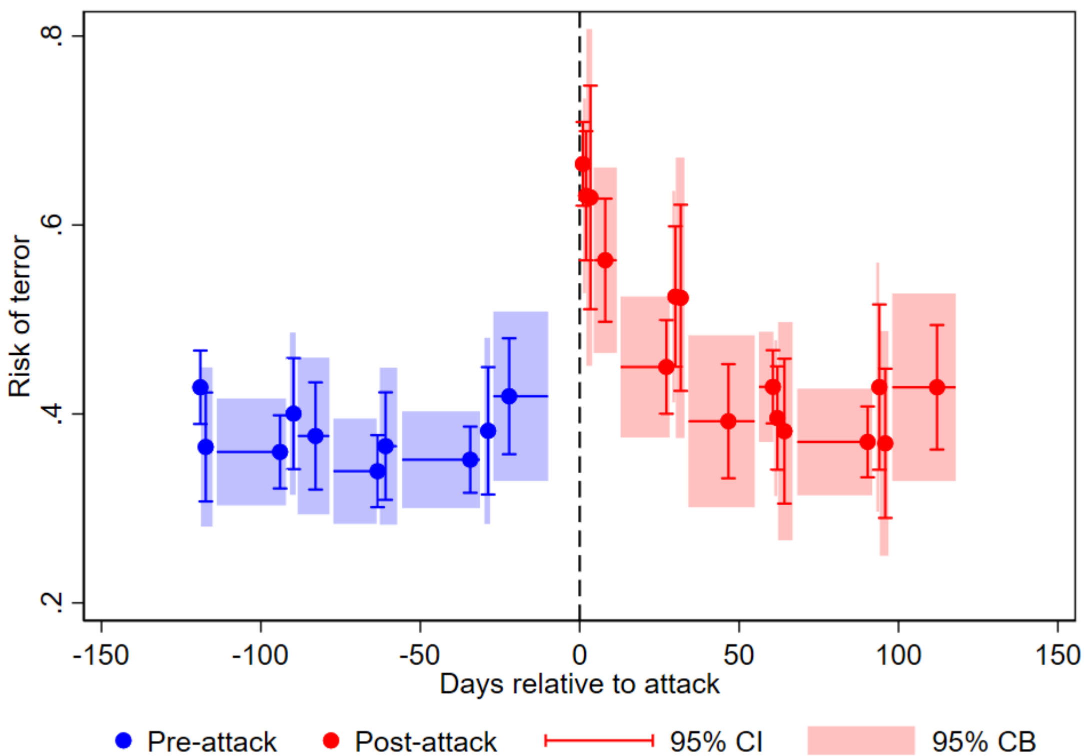
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.1c: Risk of terror: 2007 Glasgow airport attack



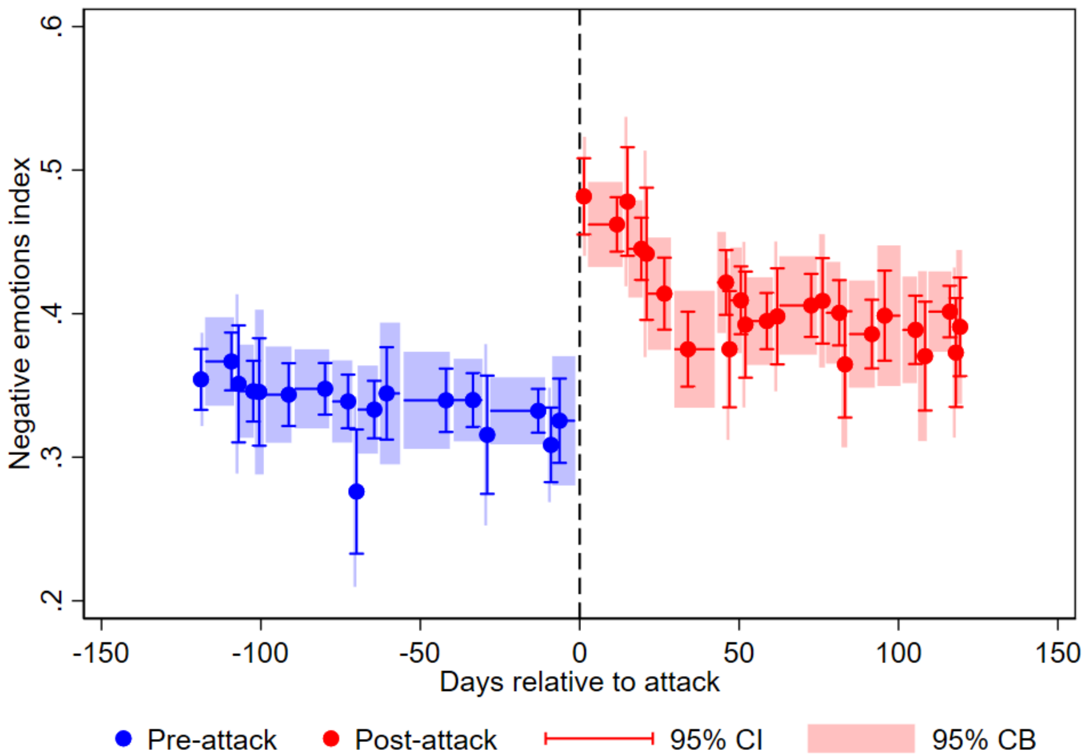
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.1d: Risk of terror: 2013 Lee Rigby murder



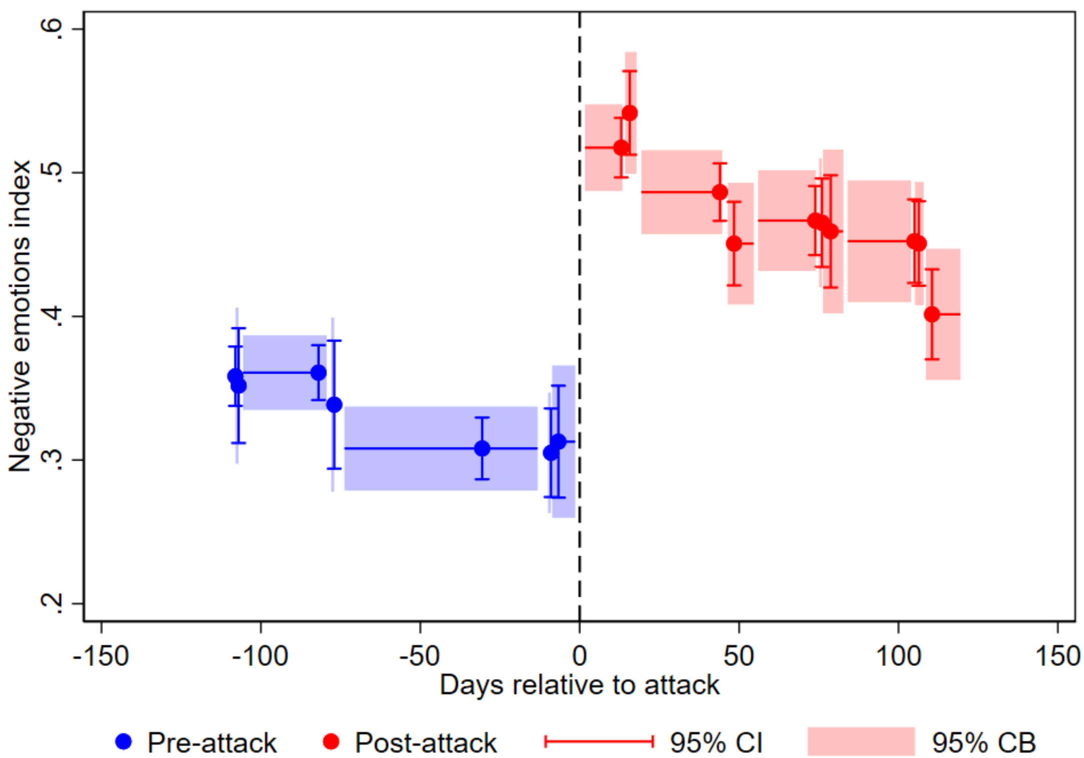
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.1e: Negative emotions index: all attacks



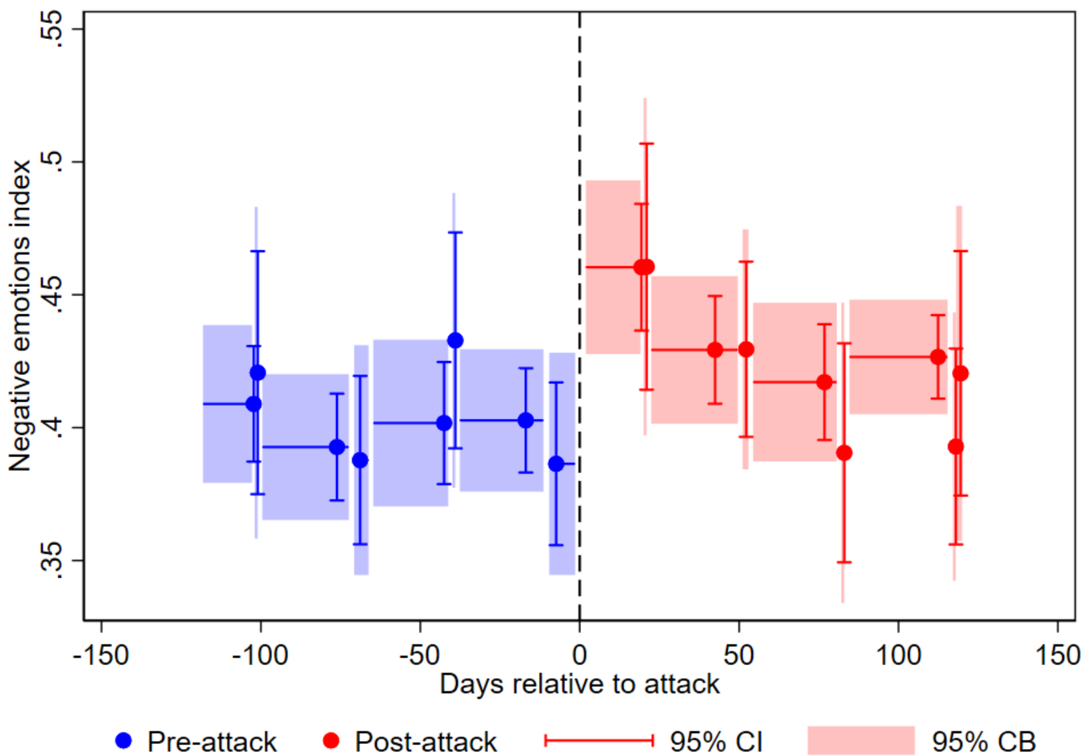
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes attack-by-region fixed effects.

Figure C.1f: Negative emotions index: 2005 London bombings



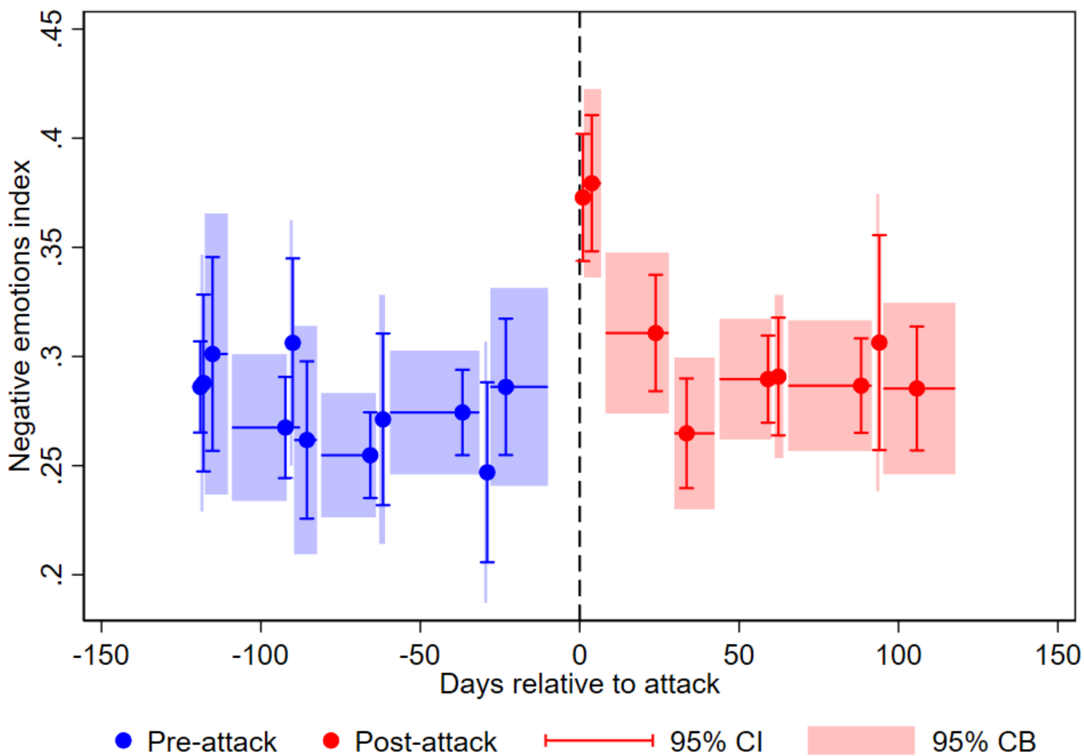
Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.1g: Negative emotions index: 2007 Glasgow airport attack



Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.1h: Negative emotions index: 2013 Lee Rigby murder

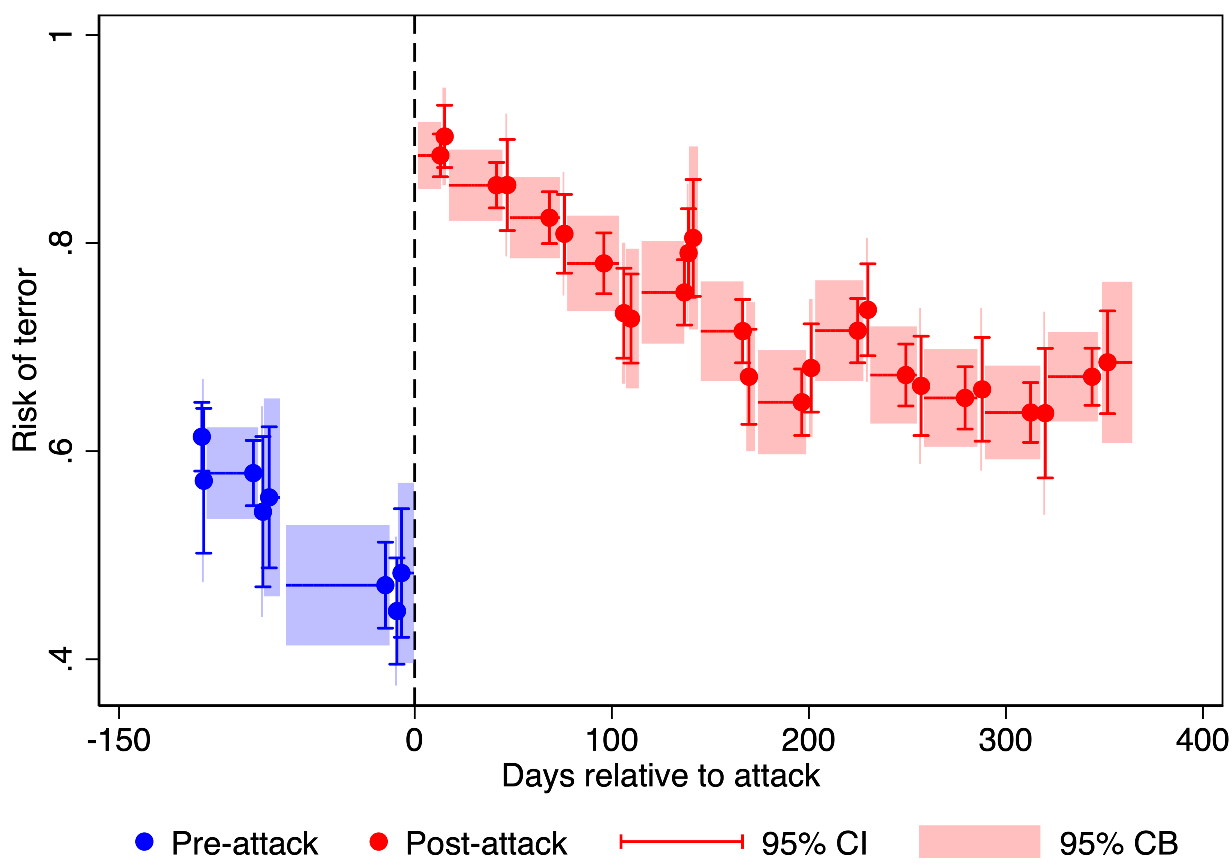


Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

C.2 Binned scatterplots for 2005 London bombings (1 year)

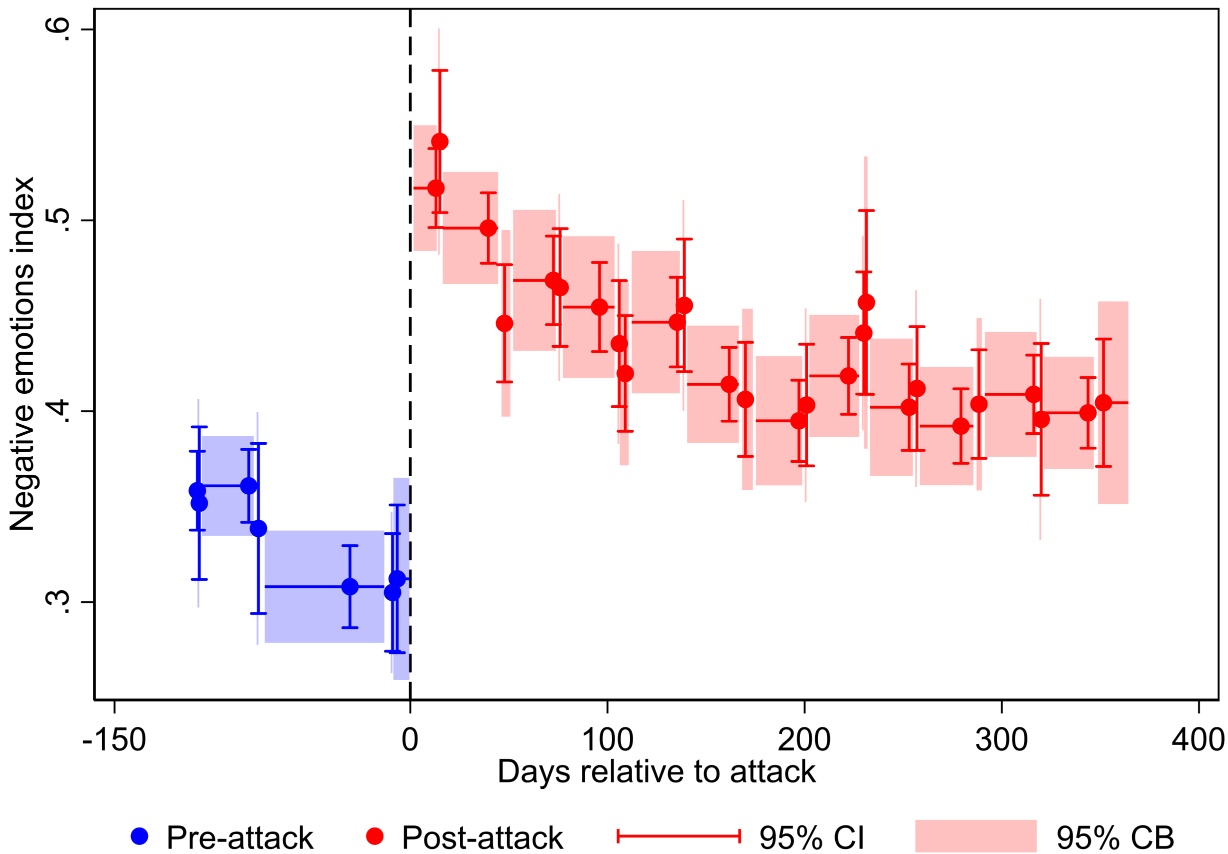
So far we have seen that the effects for the 2005 London bombings persist for up to 120 days after the attack. In this section, we plot again the binned scatterplots for this particular attack after we extend the post-attack time window to 365 days (1 year) – see Figures C.2a and C.2b below. Even though considering data for such a long time period leads to a greater potential for bias due to post-treatment national and international events, the dynamics presented in these figures provide suggestive evidence that this particular attack caused a more permanent shift in risk perceptions and negative emotions.

Figure C.2a: Risk of terror: 2005 London bombings (365 days)



Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

Figure C.2b: Negative emotions index: 2005 London bombings (365 days)



Notes: This figure shows the binned scatterplot and the corresponding confidence intervals and confidence bands, as described in Cattaneo et al. (2019b) and implemented using the `binsreg` package. The estimation includes region fixed effects.

D Full Regression Results

This section shows the full regression estimates for Figures 2, 3 and B.1a. See Table D.1 (*Risk of terror*) and Table D.2 (*Negative emotions index*) below.

Table D.1: Main results: risk of terror

	Risk of terror								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Very short run	0.255***	0.281***	0.284***						
	(0.016)	(0.023)	(0.023)						
Short run				0.248***	0.269***	0.267***			
				(0.032)	(0.032)	(0.032)			
Medium run							0.121***	0.133***	0.133***
							(0.031)	(0.032)	(0.032)
Female		0.048***			0.047***			0.048***	
		(0.015)			(0.012)			(0.011)	
Age		-0.001			-0.000			0.001	
		(0.003)			(0.002)			(0.002)	
Age squared		0.000			0.000			-0.000	
		(0.000)			(0.000)			(0.000)	
Has children		0.002			-0.004			-0.005	
		(0.019)			(0.015)			(0.010)	
Education: 15		0.116			0.078			0.024	
		(0.079)			(0.060)			(0.031)	
Education: 16		0.129			0.085			-0.002	
		(0.081)			(0.059)			(0.035)	
Education: 17-18		0.131			0.076			0.003	
		(0.079)			(0.056)			(0.033)	
Education: 19-20		0.117			0.049			-0.006	
		(0.077)			(0.058)			(0.042)	
Education: 21 or over		0.071			0.046			-0.052	
		(0.081)			(0.059)			(0.034)	
White		0.058			0.035			0.048	
		(0.051)			(0.038)			(0.028)	
Income: £5,000 to £9,999		-0.021			0.009			-0.010	
		(0.057)			(0.039)			(0.029)	
Income: £10,000 to £14,999		-0.082			-0.036			-0.025	
		(0.049)			(0.042)			(0.029)	
Income: £15,000 to £19,999		-0.016			0.014			0.006	
		(0.046)			(0.036)			(0.024)	
Income: £20,000 to £24,999		-0.024			-0.002			0.016	
		(0.043)			(0.034)			(0.026)	
Income: £25,000 to £29,999		-0.045			-0.012			0.007	
		(0.048)			(0.040)			(0.029)	
Income: £30,000 to £39,999		-0.091*			-0.037			0.003	
		(0.047)			(0.032)			(0.030)	
Income: £40,000 to £49,999		-0.059			-0.035			-0.004	
		(0.048)			(0.032)			(0.033)	
Income: £50,000 or more		-0.087*			-0.016			-0.005	
		(0.044)			(0.035)			(0.025)	
Attack × Region FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.074	0.092	0.080	0.145	0.161	0.154	0.090	0.089	0.082
Observations	4,186	3,052	3,052	6,397	4,893	4,893	13,870	10,582	10,582

Notes: This table reports the full regression results for the variable *Risk of terror*. For each time frame, we present the results of three specifications: (i) without controls; (ii) with controls; (iii) without controls but based on the same sample as in the full control specification. Standard errors are clustered at the attack-by-region level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table D.2: Main results: negative emotions index

	Negative emotions index								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Very short run	0.114***	0.124***	0.131***						
	(0.015)	(0.022)	(0.022)						
Short run				0.116***	0.134***	0.134***			
				(0.019)	(0.020)	(0.021)			
Medium run							0.065***	0.070***	0.071***
							(0.014)	(0.015)	(0.015)
Female		0.034**			0.047***			0.040***	
		(0.015)			(0.010)			(0.007)	
Age		0.005**			0.002			0.003*	
		(0.002)			(0.002)			(0.002)	
Age squared		-0.000			-0.000			-0.000	
		(0.000)			(0.000)			(0.000)	
Has children		0.001			-0.001			0.012*	
		(0.010)			(0.009)			(0.006)	
Education: 15		0.091*			0.026			0.001	
		(0.046)			(0.039)			(0.031)	
Education: 16		0.087			0.013			-0.027	
		(0.053)			(0.039)			(0.033)	
Education: 17-18		0.058			-0.021			-0.045	
		(0.050)			(0.039)			(0.032)	
Education: 19-20		-0.003			-0.053			-0.066**	
		(0.053)			(0.044)			(0.031)	
Education: 21 or over		-0.007			-0.069*			-0.107***	
		(0.048)			(0.038)			(0.031)	
White		-0.025			0.004			-0.014	
		(0.022)			(0.027)			(0.019)	
Income: £5,000 to £9,999		-0.011			0.042			0.015	
		(0.033)			(0.026)			(0.021)	
Income: £10,000 to £14,999		-0.004			0.032			0.001	
		(0.037)			(0.028)			(0.020)	
Income: £15,000 to £19,999		-0.014			0.033			0.003	
		(0.033)			(0.027)			(0.021)	
Income: £20,000 to £24,999		-0.016			0.047*			0.006	
		(0.032)			(0.025)			(0.022)	
Income: £25,000 to £29,999		-0.011			0.039			0.009	
		(0.029)			(0.024)			(0.021)	
Income: £30,000 to £39,999		-0.012			0.040*			0.003	
		(0.033)			(0.023)			(0.023)	
Income: £40,000 to £49,999		-0.034			0.002			-0.010	
		(0.034)			(0.025)			(0.021)	
Income: £50,000 or more		-0.052			0.022			-0.023	
		(0.034)			(0.030)			(0.023)	
Attack $\times$ Region FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.042	0.087	0.051	0.072	0.102	0.074	0.047	0.073	0.041
Observations	4,350	3,148	3,148	6,615	5,020	5,020	14,314	10,836	10,836

Notes: This table reports the full regression results for the variable *Negative emotions index*. For each time frame, we present the results of three specifications: (i) without controls; (ii) with controls; (iii) without controls but based on the same sample as in the full control specification. Standard errors are clustered at the attack-by-region level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E Theoretical Model

The model follows the basic setup in Becker et al. (2011) and we offer some extensions for our setting. Consider an economy that consists of individuals who consume a good (x) and are exposed to a terrorist attack. The attack provides disutility itself and via the creation of fear and anxiety, which in turn exaggerates subjective beliefs about the probability of surviving future attacks. This fear is driven by both media coverage and the severity of the attack; as captured, for example, by the number of victims. Importantly, we show how fear can (or cannot) vary over time and space in response to the attack.

Individual's expected utility is given by:

$$W = p(\tau, F) + V(x) \tag{E.1}$$

where p is the subjective probability of surviving a terrorist attack and V is the utility from consumption of good x. The subjective probability is adversely affected by the degree of terrorism, τ, and negative emotions such as fear, F. It is also reasonable to assume that the severity of an attack of terrorism and fear are mutually reinforcing with respect to the subjective probability of survival:

$$p_\tau \leq 0, p_F \leq 0, p_{\tau F} \leq 0 \tag{E.2}$$

The amount of fear one experiences is given by:

$$F(\tau, m) = f(\tau, m)(1 - T) \tag{E.3}$$

where m represents media coverage of the terrorist attack and T is a variable that represents temporal distance from an attack, such that there is a linear decay in fear over time $(0 \leq T < 1)$. Fear rises with the degree of terrorism $(f_\tau > 0)$ and it is amplified by the attention drawn to the consequences of threat through propaganda or media coverage $(f_m > 0)$. And, in the absence of terrorism, there is no fear $f(0, m) = 0$. Indeed, we can also define an alternative equation for fear that accounts for non-linearities in the response to terror:

$$F(\tau, m) = f(\tau, m)h(T) \tag{E.4}$$

where $h(T)$ captures a non-linear response (decay) of fear, which is possible because of framing effects or the responses of politicians, for instance. We can also introduce further shift parameters:

$$F(\tau, m) = f(\tau, m)(1 - T)(1 - D) \tag{E.5}$$

where D represents the geographic distance from the terrorist attack. Now, fear is moderated by the individuals temporal and geographic distance from a terrorist incident. Similarly, it is reasonable to consider aggravating factors. Specifically, it is reasonable to assume that some attacks are so severe that their impacts transcend space and time:

$$F(\tau, m) = \begin{cases} f(\tau, m)(1 - T)(1 - D) & \text{if } \ \tau \neq 1 \\ f(\tau, m) & \text{if } \ \tau = 1 \end{cases} \tag{E.6}$$

when τ is equal to 1, the most severe possible attack, the level of fear is not moderated by distance; i.e., the effects of the attack are homogeneous through space and time. Assuming a simple model of fear, as in Eq. (E.3), the expected utility is given by:

$$W^{0<T<1} = p(\tau, [f(\tau, m)(1 - T)]) + V(x), \quad W^{T=1} = p(\tau) + V(x) \tag{E.7}$$

Therefore, the expected utility is lower when an individual is temporally proximate to the terrorist attack due to the presence of fear:

$$W^{0<T<1} < W^{T=1} \tag{E.8}$$

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