CAGE

Beyond the Headlines: The intangible costs of terrorism

CAGE working paper no. 734

November 2024

Harry Pickard,
Vincenzo Bove,
Georgios Efthyvoulou,

Beyond the Headlines: The intangible costs of terrorism

Harry Pickard* Vincenzo Bove† Georgios Efthyvoulou‡

Abstract

Do terrorist attacks affect life satisfaction and mental health? To explore this question, we analyse data on all casualty-causing terrorist incidents in Great Britain from 1992 to 2020, and combine this information with individual-level data from the British Household Panel Survey and the UK Household Longitudinal Survey over the same period. To get as close as possible to a causal interpretation, we exploit variation within individuals, net of potential temporal and attack-specific unobserved factors, and report an array of different specifications and robustness tests. Our analysis reveals that geographic proximity to terrorist attacks decreases life satisfaction, particularly when the incidents occurred within the month before the interview. We also find that individuals with pre-existing mental vulnerabilities exhibit higher distress levels following a recent terrorism shock.

JEL classification: I10, I31, H56, D74
Keywords: wellbeing, life satisfaction, mental health, terrorism, security

*Corresponding Author. Address: Newcastle University Business School, Newcastle University, 5 Barrack Road, Newcastle upon Tyne, NE1 4SE, United Kingdom; Email: harry.pickard@newcastle.ac.uk

†Address: IMT School for Advanced Studies Lucca and CAGE (Competitive Advantage in the Global Economy), University of Warwick; Email: vincenzo.bove@imtlucca.it

‡Address: School of Economics, University of Sheffield, 9 Mappin Street, Sheffield, S1 4DT, United Kingdom; Email: g.efthyvoulou@sheffield.ac.uk

1 Introduction

The costs of terrorism are multidimensional, imposing social, political, and economic burdens in addition to their direct effects on security. Indeed, terrorism as a 'tactic' is intended not only to disrupt domestic security, but also to influence the psychology of the public (Cronin, 2002, p.33). The terrorism literature and policymakers alike have increasingly recognised the deleterious effects of terrorism on social cohesion (e.g., Shayo and Zussman, 2011; Arvanitidis et al., 2016; Gould and Klor, 2016; Bauer and Schulze, 2022) and economic activities (e.g., Abadie and Gardeazabal, 2003; Eckstein and Tsiddon, 2004; Gaibulloev and Sandler, 2019; Caldara and Iacoviello, 2022).

Considerably less focus has been placed on the psychological effects of terrorism on societal wellbeing outcomes, despite growing recognition that these areas are critical targets for policymaking (Frijters et al., 2020; Layard, 2021). In fact, much like crime (Dustmann and Fasani, 2016), the indirect costs of terrorism can far exceed the direct costs. Yet, quantifying these indirect costs, especially those concerning the wellbeing of entire populations, remains challenging. Declining public wellbeing, evidenced by rising stress levels reported in the World Happiness Reports since 2006 (Helliwell et al., 2023), highlights the growing challenges in managing public mental health. The indirect costs of terrorism violence on wellbeing are all the more important given the broader macroeconomic implications of mental health and the substantial welfare costs associated with mental illness (Abramson et al., 2024). Given the heightened focus and resource allocation towards counter-terrorism efforts in recent years (Mueller and Stewart, 2014), investigating this link becomes particularly pressing. The UK presents a particularly compelling case, given the mounting evidence of deteriorating mental health, especially among its youth, and the growing pressure to put wellbeing at the centre of policy design (Layard and Ward, 2020;

Blanchflower et al., 2024).[1] At the same time, the country has a long-standing history of confronting episodes of terrorism and political violence within its borders.

Against this background, this paper provides a detailed analysis of changes in individual wellbeing caused by terrorist attacks in Great Britain. Our research builds on a growing literature on the psychological effects of terrorism. Previous studies have found that terrorism triggers a 'complex state of negative arousal' comprised by a combination of negative emotions which include anxiety, fear, anger, outrage, and sadness (Fisk et al., 2019; Godefroidt, 2023). Such affective reactions can explain concomitant changes in political attitudes and electoral behaviour (e.g., Kibris, 2011; Dinesen and Jæger, 2013; Getmansky and Zeitzoff, 2014; Balcells and Torrats-Espinosa, 2018; Böhmelt et al., 2020; Epifanio et al., 2023; Vlandas and Halikiopoulou, 2024; Efthyvoulou et al., 2024). While extant research has extensively explored terrorism's impact on specific emotions, the broader psychological effects on the public remain understudied.

A limited number of studies demonstrate a marked decline in wellbeing in the aftermath of terrorist incidents (Metcalfe et al., 2011; Romanov et al., 2012; Kim and Albert Kim, 2018; Hole and Ratcliffe, 2020; Clark et al., 2020; Sønderskov et al., 2021). While insightful, these studies have largely focused on single, high-profile attacks with numerous victims (Metcalfe et al., 2011; Romanov et al., 2012; Kim and Albert Kim, 2018; Hole and Ratcliffe, 2020; Clark et al., 2020) or population subgroups (Sønderskov et al., 2021). In reality, most terrorist attacks are smaller, localised incidents involving a limited number of victims and often do not result in fatalities. Rather than large, emblematic events, attacks across the West are often carried out by lone individuals with limited resources, minimal training, and little planning.[2]

[1] David Cameron successfully pushed to establish 'wellbeing' as a metric for capturing the public's quality of life, resulting in the study of 'social wellbeing' in the Treasury's Green Book among other government publications (Layard, 2021, p.3). Similar measures have been implemented across Europe.

[2] Available here and here.

Consequently, we lack a comprehensive evidence base on how the "average" terrorist attack affects societal wellbeing. This paper takes a comprehensive approach which exploits individual-level variation in the subjective wellbeing of the general population in Great Britain over an extended period encompassing nearly 100 attacks. Unlike studies that focus on indirect indicators of wellbeing, such as specific negative emotions like pessimism (e.g., Guo and An, 2022), we employ two comprehensive wellbeing measures. Specifically, we consider a single-item measure of life satisfaction and a multiple-item measure of mental distress (Powdthavee et al., 2019; Gray et al., 2021). The former captures the cognitive or evaluative dimension of wellbeing, i.e., individuals' reflective assessments of life as a whole, whereas the latter captures the affective dimension of wellbeing, i.e., how often and intensely people experience negative emotions and elevated levels of psychological stress.

For our analysis, we leverage data from the Global Terrorism Database, covering all domestic terrorist attacks that caused deaths or injuries between 1992 and 2020. We merge the terrorism data with detailed information on individuals' characteristics and wellbeing outcomes over the same period – obtained by combining the British Household Panel Survey with the UK Household Longitudinal Survey – and produce a single dataset at the individual-wave-attack level. Following the common practice in the related literature, we create a measure of geographic proximity to attacks and use this as a proxy for exposure to terrorism. In our empirical specifications, we include individual, attack and time fixed effects to account for various sources of unobserved heterogeneity, and control for important time-varying factors that can influence people's wellbeing over time. As a result, identification in our setting comes from changes in exposure within individuals, as captured by changes in geographic proximity to between-waves attacks. Throughout our analysis, we report an extensive set of additional tests in order to convey the robustness of our results and address concerns of omitted variable bias. This allows us to get as close as possible to a causal interpretation of the reported effects and the mechanisms at play.

Our findings show a negative impact of terrorism exposure on life satisfaction, which is mainly driven by the set of 'recent' attacks that respondents have experienced in the last month before their interview. The impact is sizeable: when we compare the most exposed individuals with the least exposed ones, the estimates suggest that a geographically and temporally close attack leads to a decrease in the predicted value of life satisfaction by 0.11 units on the 1-7 scale. This explains 7% of its overall standard deviation and 14% of its within-individual standard deviation. Turning to mental health, our analysis indicates a strong dependence on initial conditions: individuals with pre-existing mental vulnerabilities exhibit higher distress levels following a recent terrorism shock, whereas those with relatively stronger mental states remain unaffected. This suggests that people with weaker emotional and psychological resilience find it more difficult to cope with the additional stressors brought on by traumatic events like terrorist attacks. When distinguishing between the three components of mental distress, we find that these effects can mostly be attributed to terrorism-induced changes in social dysfunction and confidence loss. En route, we estimate the monetary equivalent of terrorism-induced wellbeing losses, and find that an individual is willing to pay about £79 to avoid being within 100 kms of a recent attack.

The paper proceeds as follows. Section 2 discusses the data and presents the identification strategy. Section 3 examines the impact of terrorism on life satisfaction and estimates individuals' implicit willingness-to-pay to avoid exposure to terrorism. Section 4 examines the effect of terrorism on mental distress. Section 5 provides concluding remarks.

2 Empirical Design

2.1 Data, samples and key variables

We use individual-level data from the British Household Panel Study (BHPS) and its successor, the UK Household Longitudinal Study (UKHLS), also known as Understanding Society. This is a nationally representative longitudinal survey of households in Great Britain (England, Scotland, and Wales)[3] that provides information on various aspects of people's lives, including their finances, political preferences, social attitudes, health and wellbeing. Household members are interviewed annually in successive waves (starting in 1991) and their responses can be linked to the Middle Layer Super Output Area (MSOA) they reside.[4] The longitudinal nature of BHPS-UKHLS allows for the tracking of individuals over time, providing valuable insights into life course dynamics and the impact of policy interventions and unexpected events on attitudes and behaviour.

Following recent empirical studies (see, e.g., Powdthavee et al., 2019; Gray et al., 2021), we capture an individual's level of subjective wellbeing using two variables: *Life satisfaction* and *Mental distress*. The measure of life satisfaction is based on the following BHPS-UKHLS question, which is worded in the same way across waves: "How dissatisfied or satisfied are you with your life overall?". Responses are coded on an ordinal scale from 1 to 7, where 1 corresponds to 'not satisfied at all' and 7 to 'completely satisfied'. The measure of mental distress is based on 12 items from the negative affect scale of the General Health Questionnaire (GHQ). Respondents are asked how often (on a four-point category scale) over the past few weeks they: had lost sleep over worry; felt constantly under strain; felt

[3]Our analysis excludes Northern Ireland, given its long history of colonisation and sectarian division, which makes the impact of terrorist events very distinct compared to the mainland. In addition, Northern Ireland was not included in the BHPS-UKHLS data until 2002.

[4]MSOAs comprise between 2K and 6K households and have a residence population between 5K and 15K people.

they could not overcome difficulties; been feeling unhappy and depressed; been losing confidence; been feeling like a worthless person; were playing a useful part in things; felt capable of making decisions; been able to enjoy day-to-day activities; been able to concentrate; been able to face up to problems; and been feeling reasonably happy. The answers to each individual question are given a value 0 to 3 and then all 12 questions are added together to produce a single measure of mental distress, with the lowest distress level scoring 0 and the highest distress level scoring 36.

Data on terrorist attacks are obtained from the Global Terrorism Database (GTD), the most comprehensive database on terrorist events around the world from 1970 through 2020. We consider the universe of casualty-causing attacks[5] that occurred in Great Britain during the BHPS-UKLS data collection period. This covers a spectrum of terrorist incidents across space and over time, such as the 1996 Manchester bombing, the 2005 London bombings, the 2007 Glasgow Airport attack, the 2016 murder of MP Jo Cox in Yorkshire, and the 2020 Reading stabbings. Section A.1 in SI Appendix offers background material for the attacks considered in our analysis.

Following Efthyvoulou et al. (2024), we combine the longitudinal survey data with the terrorism data and produce a single dataset at the individual-wave-attack level. To achieve this, we assign attack a to wave w for individual i, if the attack took place between the end date of the previous wave $w - 1$ and the date of individual i's interview in wave w.[6] In other words, for each individual–wave observation in BHPS-UKHLS, the dataset includes one row for every attack that occurred between these two dates. Given the attacks' high-profile nature and abundant news coverage, we assume that a respondent was *potentially* exposed to all assigned attacks at the time of the interview. To avoid measurement errors

[5]Casualty-causing attacks are those resulting in at least one person wounded or killed.

[6]Section A.2 in SI Appendix provides a hypothetical example illustrating the process of constructing the individual–wave–attack level dataset.

and account for the possibility that the news may take some hours to spread, we exclude observations where the attack occurred on the same date of the interview. Furthermore, to remove outliers in the temporal distance between attacks and interviews, we exclude a very small number of observations (<2%) that correspond to attacks that occurred more than one year before the interview date. Finally, to ensure that the individuals in our sample are always tied to the same location baseline, we drop observations where the respondent is defined as a "mover" in wave w; that is, when they are observed in a different MSOA compared to the last wave they were interviewed.

This procedure results in two different samples, one for each wellbeing measure. Sample 1 includes wave-on-wave data on *Life satisfaction* (i.e., individual-specific responses to the life satisfaction question in both waves w and $w - 1$), the assigned attacks, and a wide set of control variables. This contains information on 53,511 individuals, 18 survey waves, and 67 attacks over the period 1998-2020 (1,032,722 observations in total). Sample 2 includes the corresponding data on *Mental distress*, and contains information on 56,747 individuals, 24 survey waves, and 97 attacks over the period 1992-2020 (1,298,976 observations in total).[7] Descriptive statistics of our key variables are provided in Table 1.[8] As can be seen in this table, the average life satisfaction is 5.2 with a standard deviation of 1.4 (on the 1-7 scale), whereas the average mental distress is 11.2 with a standard deviation of 5.4 (on the 0-36 scale). Across the years, the two measures are relatively stable, with no major changes in their average values before or after specific waves (see SI Appendix Figure A.3).

To proxy exposure to terrorism, we geo-locate the attacks and calculate the distance in kilometres (kms) between the centroid point of an individual's MSOA of residence and

[7] Put differently, in sample 1 (sample 2), individuals have 5 (6) observations, on average, across all survey waves and are assigned to 4 (4) attacks, on average, per wave.

[8] See also Table A.4 in SI Appendix for an extended version of Table 1 that includes the full set of variables used in our analysis.

the location point of each one of the assigned attacks. The intuition is that, for any given individual, an attack occurring closer is more consequential – and thus should have a more detrimental effect on their wellbeing – compared to one that occurs at a more distant location.

The use of geographic proximity as a measure of exposure to terrorism is a standard practice in the literature (see, e.g., Kibris, 2011; Getmansky and Zeitzoff, 2014; Nussio et al., 2019; Bove et al., 2022; Falcó-Gimeno et al., 2023). Residing close to a terrorist attack intensifies negative emotions and threat perceptions; i.e., people believe there is a high risk of future attacks in the same or nearby areas (Falcó-Gimeno et al., 2023). It also amplifies perceptions of personal vulnerability (Braithwaite, 2013), fosters 'counterfactual thoughts', wherein individuals imagine they could have been the victims if circumstances had been slightly different (Zagefka, 2018), and affects the amount of coverage the event receives from local media (Böhmelt et al., 2020). SI Appendix Figures A.1.1 and A.1.2 present the geographic and temporal distribution of the attacks considered in our analysis. Not surprisingly, Greater London is the part of the country with the highest exposure to terrorism. However, several attacks also occurred outside of London, spread across the mainland, with the distance between each MSOA and each attack having an average value of about 230 kms and a standard deviation of about 155 kms.

2.2 Identification strategy

Our empirical approach makes it possible to estimate the average (combined) effect of multiple terrorist attacks over an extended period of time, and explore heterogeneities with respect to individual and attack characteristics. To do that, we follow the studies of Falcó-Gimeno et al. (2023), who leverage variation in the location and timing of attacks to examine the impact of terrorism on regional-level outcomes, and Efthyvoulou et al. (2024), who extend this framework to individual, survey-based data.

Specifically, our model specification takes the following form:

$$\textit{Wellbeing}_{iwa} = \beta_1 \textit{Exposure}_{iwa} + \beta_2 \mathbf{X}_{iwa} + \theta_i + \lambda_a + \phi_{wt} + \varepsilon_{iwa} \tag{1}$$

where $\textit{Wellbeing}_{iwa}$ denotes self-reported wellbeing (*Life satisfaction* or *Mental distress*) for individual i, as recorded in wave w, after attack a was perpetrated; $\textit{Exposure}_{iwa}$ captures geographic proximity of individual i, interviewed in wave w, to each attack a (reverse of the log of distance in kilometres, standardised); $\mathbf{X}_{iwa}$ is a vector of individual-level control variables; θ_i, λ_a and ϕ_{wt} represent individual, attack, and wave $\times$ week fixed effects, respectively (where t is the week of the year during which the data was collected); and, ε_{iwa} is an error term clustered at the individual level. The inclusion of θ_i, λ_a and ϕ_{wt} accounts for individual time-invariant and other temporal and attack-specific unobserved factors. As a result, identification in this setting comes from changes in exposure within individuals, as captured by changes in geographic proximity to between-waves attacks. To provide evidence that terrorism results in lower levels of subjective wellbeing, the coefficient on *Exposure* (β_1) must have a negative sign in the regressions of *Life satisfaction* and a positive sign in the regressions of *Mental distress*.

Although terrorist incidents can cause significant shifts in self-reported wellbeing, we expect that time will play a crucial role in moderating these effects. Much of the extant literature suggests that the emotional responses to collective traumatic events are transient: they fade quickly as individuals habituate and return to a state of homeostasis or baseline arousal after around 4-6 weeks (Pennebaker and Harber, 1993; Maguen et al., 2008; Brewin, 2001; Rauch et al., 2022). This appears to align with the conclusions of recent analyses on terrorism, which indicate that the emotional and risk-assessment impacts of terrorist events are temporary, often subsiding within a month (see, e.g., Epifanio et al., 2023; Bove et al., 2024).

Given that the "typical, average attack" in our analysis involves a small number of victims,[9] we expect the effects on wellbeing to last – or to be far more pronounced – in the first post-attack month. To test for this, we run separate regressions for the attacks occurring 1-30 days before the date of the individual i's interview in wave w, and those occurring outside this time window. The intuition is that geographic proximity should only matter in the short period after a terrorist event, and thus the effects should only be evident in the set of survey respondents who have a 'fresh memory' of it.

2.3 Endogeneity and selection issues

If we regress individual wellbeing on local exposure to terrorism, a number of endogeneity issues may arise. First, it is possible that localities (MSOA) with greater exposure to terrorism, and consequently the characteristics of their residents, may differ systematically from those with lower exposure. Including individual fixed effects in Eq. (1), while ensuring that the individuals in our sample are always tied to the same location baseline, allows us to eliminate such time-invariant sources of individual heterogeneity. Second, time-varying individual characteristics may confound the relationship between exposure and wellbeing. Adding vector $\mathbf{X}_{iwa}$ in Eq. (1) accounts for the most important individual-specific time-varying factors that can influence people's wellbeing over time; including age, income, education, job status, marital status, and the presence of children in the household (see Table A.4 in SI Appendix for the full list of control variables). To further address this issue, we calculate how strong the selection on unobservables would have to be in order to explain the observed relationship.

Another relevant concern comes from the possibility that the location of terrorist at-

[9]For instance, only 22% of the sampled attacks resulted in more than ten casualties, and only 7% of them caused death to more than three people.

tacks is linked to time-variant regional characteristics that also shape wellbeing.[10] To mitigate this concern, we test for the presence of pre-existing trends that differ according to the degree of exposure to terrorism. Along these lines, we also check whether our results persist when we control for the MSOAs that were directly hit by the attacks, and when we account for the geographic proximity to London (the country's capital city and the most frequently targeted area). Finally, one might argue that the individuals who are most affected by the attacks may not want to be interviewed in the next waves, which could bias the wellbeing responses. To reduce the risk of selection bias affecting our estimates, we perform the same analysis using the sample of BHPS-UKHLS respondents who appear in at least five waves of the survey.

We believe that our empirical strategy, combined with these additional checks, can address the most important identification threats, allowing us to get as close as possible to producing causal parameters and measuring the pure effect of terrorism on wellbeing.

3 The Effect of Terrorism on Life Satisfaction

3.1 Key findings

Table 2 presents the results of estimating Eq. (1) for *Life satisfaction*. We start from a specification that includes our exposure measure, together with individual and attack fixed effects (column (1)), and we then add temporal fixed effects and the control variables in a progressive manner (columns (2)-(3)). Finally, we test the sensitivity of our estimates to augmenting the models with the lagged value of the outcome variable; that is, the individual's response to the life satisfaction question as recorded in the previous wave (columns

[10]It should be stressed that the timing of violent events, such as the assassination of political leaders and terrorist attacks, is considered to be exogenous and largely randomly assigned relative to that of the interviews in a survey (Muñoz et al., 2020).

(4)-(6)). We can see that exposure (geographic proximity to attacks) exerts a negative and significant effect on life satisfaction, providing some first evidence of a terrorism-induced wellbeing loss for exposed individuals. We can also see that the estimates and standard errors are the same across the six specifications, suggesting that there is no difference to the interpretation of the results if one controls for common temporal shocks, changes in individual characteristics, or individual-specific time trends.

How large is this wellbeing loss? When we compare the most exposed individuals with the least exposed ones, our estimates suggest that a geographically close attack leads to a decrease in the predicted value of life satisfaction by 0.03 units; that is, a decrease that amounts to 2% of its overall standard deviation and 4% of its within-individual standard deviation. To gain further insights about the magnitude of this effect, we benchmark our results against those of major individual life events. According to our estimates, the 0.03-unit effect is roughly 10% of the immediate effect of losing one's job, 7% of becoming newly long-term sick/disabled and 10% of becoming newly widowed.[11] This is quite substantial, especially when considering that it captures the average effect for all people living in close proximity to attacks – of which the overwhelming majority do not experience direct victimisation – while the effects of major life events relate only to those who are directly affected.

As noted in Section 2.2, the perturbation due to terrorist attacks is expected to fade quickly and subside within a month, similar to the impact of other collective traumatic events. This implies that the main driver of the negative effects observed in Table 2 is the set of terrorist events that respondents have experienced in the last month before their interview. In Table 3, we estimate the same models as before but we now make a distinc-

[11] We calculate the effects using a binary indicator that takes value 1 in the first wave in which there is a change in the individual's respective circumstances. More details and estimates for other life events can be found in Section A.5 of SI Appendix.

tion between 'temporally distant' attacks (those that occur more than 30 days before the interview) and 'recent' attacks (those that occur within 30 days before the interview).[12] The results confirm the important role of time in conditioning the wellbeing responses: exposure to terrorism one month before the interview produces a large and significant detrimental effect on life satisfaction, while exposure to terrorism 2-12 months before the interview does not seem to have any effect.[13] The absence of long-lasting wellbeing losses does not mean, however, that terrorism can be ignored. In fact, while a terrorist incident may not cause a persistent reduction in life satisfaction, it does represent a repeated shock and residents are permanently exposed to such shocks (Dustmann and Fasani, 2016). In other words, even if individuals recover completely from each incident, a significant portion of the population – those living in close proximity to areas that were recently hit by attacks – will experience lower levels of life satisfaction in a given period (than they would without these incidents), and this can have important repercussions for their behaviour, productivity, and relationships.

Qualitatively, the effects for recent attacks (columns (4)-(6) of Table 3) are 3.5 times as large as those reported in Table 2. Specifically, when we compare the most exposed individuals with the least exposed ones, the estimates suggest that a geographically and temporally close attack leads to a decrease in the predicted value of life satisfaction by 0.11 units, which explains 7% of its overall standard deviation and 14% of its within-individual standard deviation.[14]

We next explore whether the reduction in life satisfaction in the aftermath of recent

[12]Put differently, for each individual–wave observation in BHPS-UKHLS, the dataset for 'recent' attacks includes one row for every attack that occurred in the last 30 days before the individual's interview; i.e., we consider one month as a time window to terrorism exposure.

[13]In Table 3, we report estimates when the lagged value of the outcome variable is included among the regressors. The results do not change if this is omitted from the models.

[14]We are unable to benchmark the 30-day effect against other life events because we do not know the precise timing at which they occur between two waves.

attacks is a unique phenomenon of a certain type of individuals. For instance, people who already feel that their life is falling short in some meaningful way might be more affected by a terrorism shock. In Table 4, we test whether initial conditions in life satisfaction matter for the empirical relationship we uncover. To do that, we consider interviewees' assessment as to how they felt about their life the first time they were interviewed, and interact exposure (to recent attacks) with binary indicators that split individuals into groups based on different cut-off points of the initial values.[15] The estimates obtained do not support the presence of asymmetric effects along this dimension: in all cases, the interaction term enters the specification with a negative sign but fails to reach statistical significance. Similar (insignificant) results are also obtained when we consider heterogeneity with respect to other individual characteristics (see Section B.9 in SI Appendix).

3.2 Identification tests

As mentioned in Section 2.3, if self-reported wellbeing is influenced by unobserved time-varying factors that are also correlated with the location of terrorist attacks, omitted variable bias would prevent the identification of a causal effect. The stability of our estimates across different specifications is quite reassuring as regards to biases arising from the potential omission of unobserved individual characteristics. To quantify this, we follow Altonji et al. (2005) in calculating how strong the selection on unobservables would have to be in order to invalidate the observed effects. By comparing the estimates of *Exposure* in Table 3 before and after the inclusion of vector $\mathbf{X}_{iwa}$ (columns (5)-(6)), we find that unobserved factors would need to exert at least 11 times the influence of observed factors (such as changes in age, education, income, and employment status) to explain away the entire

[15]Note that the distribution of life satisfaction is highly skewed to the left with 50% of the observations corresponding to the top 2 values (6 and 7), and less than 30% of the observations corresponding to the bottom 4 values (1-4).

effect of recent attacks on life satisfaction. Such a strong role of unobserved individual characteristics is very unlikely.

To further address concerns of omitted heterogeneity, we perform two straightforward – but powerful – falsification exercises. First, we regress past life satisfaction on future exposure to terrorism by replacing $Wellbeing_{iwa}$ in Eq. (1) with its 'lagged value'. A statistically significant estimate in these regressions would indicate the presence of pre-existing trends; that is, omitted time-varying factors (possibly at the regional level) causing heterogeneous dynamics in wellbeing between high-exposure and low-exposure individuals, which cannot be attributed to the timing of recent attacks (Efthyvoulou et al., 2024). Second, we estimate the same regression setup using a placebo outcome variable: a 'related' variable that should not be directly affected by terrorism. To do that, we rely again on BHPS-UKHLS data and consider responses to a question capturing perceptions of current financial wellbeing ("How well would you say you yourself are managing financially these days?"; 1-5 scale). A statistically significant estimate in this case would imply that our exposure measure is linked to unobserved factors that influence all aspects of people's lives (including their financial situation), and would cast doubt on our argument that terrorism shapes life satisfaction solely through shifts in emotional states and everyday habits.

Table 5 presents the results of these two exercises based on the 30-day time window to terrorism exposure. The estimates are substantially smaller than those in Table 3 and none of them turn out to be statistically significant in any of the specifications. This contributes to supporting a causal interpretation of our findings and the mechanisms at play.

3.3 Further robustness tests

The key finding that emerges from our analysis is that exposure to recent terrorist attacks has a detrimental impact on self-reported life satisfaction. To ensure robustness and gain further insights into this finding, we consider a wide range of supplementary analyses, detailed in Section B of SI Appendix.

We start by conducting additional tests to alleviate concerns about omitted heterogeneity related to the attack locations. In Section B.1, we augment Eq. (1) with a variable capturing the MSOAs that were directly hit by recent attacks, whereas in Section B.2, we include a control for the proximity between the individual's MSOA and London. Our estimates remain unaffected, indicating that living in the attacked MSOA or near London does not distort the impact of our measure of exposure. Similar results are also obtained when we drop individuals residing in Scotland and/or Wales, where terrorist incidents are less frequent, and wellbeing may be influenced by distinct, country-specific dynamics (see Section B.3).

In Section B.4, we replicate the same analysis for respondents who participated in at least five waves of the survey. Individuals personally affected by attacks (e.g., those with family members involved) may opt out of future waves, which could lead to an underestimation of the true impact of terrorism on wellbeing. The estimates obtained from this exercise are consistent with those in Table 3, suggesting that our results are not driven by individuals with short survey participation.

In Section B.5, we check sensitivity to employing a 'closest-attack-between-waves strategy' (Efthyvoulou et al., 2024). Specifically, we let each individual to be exposed to only one recent attack per wave – the nearest one geographically – and estimate the same models as before. Once again, we find strong evidence of a negative relationship between terrorism exposure and life satisfaction. This deals with the concern that our results may be affected by the decision to assign multiple attacks to each respondent in each wave.

In Sections B.6, B.7 and B.8, we experiment with three variations of the baseline model. First, we control for residual temporal heterogeneity by incorporating day fixed effects or time distance fixed effects. Second, we check robustness to using an alternative clustering of standard errors, at the MSOA level. Third, we rely on a different measure of terrorism exposure that divides geographic distance into deciles. In all cases, the core relationship holds and our inferences do not change.

In Section B.9, we interact exposure with a binary indicator that splits individuals into groups based on gender, age, ethnicity, and internet usage. The interaction term fails to reach statistical significance across all four specifications, suggesting that there is no clear heterogeneity in the effects with respect to the aforementioned individual characteristics.

Finally, in Section B.10, we examine whether the intensity of threat moderates the observed relationship. To do that, we estimate models that include an interaction with the type of victim, distinguishing between deadly and non-deadly attacks. Terrorist events that cause deaths – and not just injuries – can amplify the shock value and the sense of fear and insecurity among the population (Bove et al., 2022; Falcó-Gimeno et al., 2023), and this can potentially lead to larger wellbeing losses in their aftermath. The evidence obtained supports this argument: even though both deadly and non-deadly attacks appear to be harmful for people's life satisfaction, the effects are relatively stronger (both economically and statistically) for the former type.[16]

3.4 Assessing the indirect costs of terrorism

Security, or the absence of terrorism, is a fundamental public good that must be balanced against other public goods. When the costs imposed on people by terrorist acts are known, governments can make better informed decisions about how much to invest in counter-terrorism policies. In this section, we use the 'life satisfaction approach' to assess the indirect costs of terrorism in the UK. This approach correlates the degree of public goods (or

[16]Using other proxies to gauge the event's severity (e.g., dividing attacks by the number of casualties) produces similar results. It is important to note that the severity of an attack is closely linked to other idiosyncratic characteristics, such as the target, the method used, and the amount of media attention that the event receives in its aftermath. This strong correlation makes it difficult to disentangle individual effects and to assess the relative importance of the various conditioning (attack-specific) factors.

public bads) with individuals' reported subjective wellbeing and evaluates them in terms of life satisfaction, as well as relative to the effect of income (Frey et al., 2007; Dolan et al., 2019). Specifically, we use our estimates to calculate an individual's implicit willingness-to-pay (WTP) to avoid exposure to terrorism – how much income a person would sacrifice to hold their wellbeing constant – and then translate this value into an aggregate figure at the city level. Previous attempts to calculate WTP for terrorism relied mostly on cross-sectional data in which causal evidence is limited, or employed other approaches. For instance, Smith et al. (2008), using a conjoint survey, found that US individuals have a positive WTP for an anti-terrorism defence policy between \$100 and \$220 annually.

To simplify the interpretation, we replicate our main analysis using a binary version of the exposure measure that equals 1 when an individual resides within 100 kms of an attack that occurred in the last 30 days.[17] The estimates, reported in SI Appendix Table A.5.2, suggest that being within this geographic area reduces life satisfaction by 0.019 units on the 1-7 scale. We then take an established coefficient for income from the literature: log annual gross household income is estimated to raise life satisfaction by approximately 35% of a standard deviation (Sacks et al., 2010). This corresponds to an increase of 0.508 points in our life satisfaction measure (standard deviation of 1.452). The median gross annual income in 2021 for all workers in the UK (full-time and part-time) was £25,971 (ONS, 2023), which is equivalent to £2,134.60 for the 30-day period in which the terrorism effect is active. A one percent change in income (about £21), therefore, raises life satisfaction by approximately 0.00508 points. This implies that an individual is willing to pay £$(21 \times 0.019)/(0.00508) =$ £78.52 to avoid being within 100 kms of an attack that occurred in the last 30 days. Multiplying this figure (i.e., individual WTP) by city adult population allows

[17] To put this into perceptive, the 100-km distance is equivalent to the longest physical distance across Greater London (about 60 kms) plus the surrounding areas. This allows us to capture the fact that terrorism produces spillover effects on people who live in neighbouring areas (Falcó-Gimeno et al., 2023).

us to calculate the city-specific aggregate WTP. Table 6 displays the corresponding figures for the main 20 cities in the UK.

These monetary values, however, do not account for the city's history of terrorism – an important consideration due to the uneven geographical distribution of terrorist events. Individuals living in cities which are less frequently exposed to casualty-causing terrorist incidents are expected to have a lower WTP. To account for this, we multiply the individual and aggregate WTP values by the average number of attacks occurring within 100 kms of a city's centroid *per year* over our sample period. This produces the yearly city-specific adjusted WTP values reported in Table 6. As can be seen in this table, the monetary equivalent for terrorism-induced wellbeing losses ranges from £695 thousand in Plymouth to £386 million in London annually. This indicates that the indirect costs of terrorism may far exceed the direct (economic) costs.[18]

4 The Effect of Terrorism on Mental Distress

4.1 Key findings and identification tests

We now turn to explore the effects of terrorism on the affective dimension of wellbeing: an individual's level of mental distress. Panel A of Table 7 reports the results of estimating the same regression setup as in Table 2, with *Mental distress* as the dependent variable. The estimates have the expected positive sign – implying that exposure to terrorism raises distress levels – but they are mostly statistically insignificant; e.g., when stricter specifications are used. Separating attacks based on their time proximity to the interview date also fails to reveal a clear detrimental effect on mental health. As can be seen in panel B of Table 7, the exposure estimates for attacks that took place in the last month are three

[18] For instance, the total economic costs of five terrorist attacks that took place in the UK in 2017 were about £172 million. Available here.

times as large as those for attacks that happened further in the past; however, they remain statistically insignificant throughout.

The sizeable, but imprecisely estimated, effects of recent attacks could potentially be explained by the fact that only a portion of the population experiences heightened mental distress when faced with a terrorism shock. A factor that is strongly linked with mental health deterioration following traumatic shocks is the presence of pre-existing conditions. Individuals who already suffer from mental health disorders are more likely to experience worsening symptoms after a traumatic event because their ongoing stress makes it harder for them to regulate their emotions or employ effective coping strategies (Bryant, 2019). To test this argument, we interact exposure with indicators that identify respondents who displayed relatively 'poor' mental health the first time they were interviewed. Since the GHQ score is a subjective and self-reported measure, we experiment with three alternative sets of individuals: (i) those with an initial distress score above 8 (corresponding to the highest two-thirds of the score distribution), (ii) those with an initial distress score above 10 (above the median), and (iii) those with an initial distress score above 12 (corresponding to the highest one-third of the score distribution).

The results suggest that people with pre-existing conditions are indeed more susceptible to experiencing mental health deterioration after a terrorist attack. As can be seen in Table 8, exposure exerts a positive and significant effect on distress for people with mental vulnerabilities (as inferred from the sum of the estimates of *Exposure* and the interaction term), and this effect vanishes, or even changes direction, for people with stronger mental state (as inferred from the estimate of *Exposure* alone). Qualitatively, the effects are maximised when we focus on individuals in the top tertile of initial distress (scores above 12). This is further validated through our analysis of the continuous version of initial conditions (see Section C.3 in SI Appendix), and aligns with studies in psychology, which consider GHQ scores above 11 or 12 as indicative of 'mental illness' (see, e.g., Goldberg et al., 1997). When we rely on individuals in this group and compare those with the highest exposure to those with the lowest, the estimates suggest that a geographically and temporally close attack leads to an increase in the predicted value of mental distress by 1 unit. This explains 19% of its overall standard deviation and 36% of its within-individual standard deviation.

To strengthen the credibility of our results, we perform the two falsification tests of Section 3.2. First, we replicate the regressions of Table 8 using the lagged mental distress as the dependent variable. Second, we experiment with a placebo outcome variable; namely, the respondent's physical health, as captured by the Physical Component Summary (PCS) score.[19] Although ongoing mental health issues and chronic stress can eventually lead to various physical health problems, the psychological reactions that individuals experience right after a terrorist attack are not expected to produce immediate physical symptoms that can be easily seen or measured. As shown in Table 9, both exercises return estimates which are smaller and statistically less robust than those reported in Table 8, allowing us to rule out the possibility that our results are driven by pre-existing trends, or unobserved factors related to physical health.

4.2 Decomposing the effects

We now turn to the question of whether the heightened distress experienced by individuals with pre-existing mental vulnerabilities, as established above, stems from specific dimensions of psychological state. To address this question, we adopt Graetz (1991)'s disaggregation of the GHQ index into separate and clinically meaningful factors, and construct the three sub-indices of mental distress: *Social dysfunction*, *Anxiety and depression*,

[19]This is a summary score for the individual's physical health status, derived from four key domains: physical functioning, role limitations due to physical health problems, bodily pain, and general health perceptions. The PCS score is calculated on a scale from 0 to 100, with higher scores indicating better physical health.

and *Confidence loss*. If anything, one would expect terrorism to affect all domains of mental health. Individuals in affected areas might distance themselves from social interactions due to fear of public places, mistrust of others, or a broader sense of insecurity, making it harder for them to manage daily tasks. At the same time, the fear triggered by acts of terrorism and the uncertainty about potential future attacks can exacerbate anxiety and depressive symptoms. Finally, the unpredictable nature of terrorism can result in a loss of self-confidence and a sense of inadequacy, as individuals may feel unable to protect themselves or influence their environment.

Figure 1 presents the marginal effects of exposure for individuals with low and high levels of initial distress (as captured by the variable *Initial value* [*>12*]), both when using the overall measure and when it is replaced by each of the three components.[20] Our estimates indicate that geographic proximity to terrorist events intensifies social dysfunction and confidence loss in individuals who already have high initial levels of these factors. The third one – anxiety and depression – is also affected but to a lesser extent. This is in line with the study of Metcalfe et al. (2011), who find that the 9/11 attacks had the largest impact on social dysfunction measures, such as the enjoyment from day-to-day activities and the ability to make decisions and face problems. Our estimates also show no effects across all domains of mental distress for individuals with healthier mental states, suggesting that these people have more resources to draw upon in times of negative shocks.

4.3 Further robustness tests

We probe the robustness of the results for *Mental distress* (as presented in Table 8) through a large number of auxiliary analyses, detailed in Section C of SI Appendix. First, we restrict the sample to include the same individual-wave-attack observations as in the case of

[20]For comparability purposes, we use the standardised value of all four indices.

Life satisfaction, which allows us to address concerns about the comparability of the results across the two wellbeing measures (see Section C.1). Second, we check sensitivity to using an alternative specification of the outcome variable, based on the 0-12 Caseness scoring method instead of the 0-36 Likert scoring method (see Section C.2). Third, we examine whether the significant role of pre-existing mental vulnerabilities is confirmed when using the continuous version of the initial-conditions variable (see Section C.3). Finally, we perform the same set of tests and supplementary analyses as those described in Section 3.3 for life satisfaction (see Section C.4). Overall, the evidence obtained does not alter our key findings.

5 Conclusions

We explore the indirect costs of terrorism in Great Britain by estimating how terrorist violence affects individual wellbeing, measured by life satisfaction and mental distress. We combine data on all casualty-causing terrorist incidents over the period 1992–2020 with individual-level information from BHPS-UKHLS, and analyse variation within individuals, net of potential temporal and attack-specific unobserved factors.

Two key findings emerge. First, geographic proximity to terrorist attacks decreases life satisfaction, particularly when the incidents occurred within the month before the interview. Although individual acts of terrorism do not appear to have persistent effects on life satisfaction, the recurrent nature of terrorism implies that residents are permanently exposed to such shocks, and that a significant portion of the population is affected during any given period. This can have important, and potentially long-lasting, negative impacts on behaviour, productivity, and interpersonal relationships. Second, while terrorism does not significantly affect the mental health of the general population, individuals with pre-existing mental vulnerabilities exhibit heightened distress following recent attacks. Life satisfaction, as a broad evaluative measure, and an immediate reflection of current life conditions, appears more susceptible to the impact of sudden, disruptive events – especially those that challenge perceptions of stability and safety for everyone. The generalised sense of insecurity that terrorism instils directly affects how people evaluate their lives. In contrast, mental health, and thus individuals' affective states such as emotions, moods, and stress levels, appear more responsive to the vulnerability of the individual, with those already experiencing distress being more susceptible to further harm. These differences reveal important inequalities in terrorism's impact and highlight the more individualised nature of mental health deterioration and the broader, collective shifts in life satisfaction.

This study represents a first attempt to detect a causal impact of the "average" terrorist attack on wellbeing. Yet, there are a number of limitations, and we hope that some important avenues for further research might emerge from these limitations. First, we focus solely on Great Britain, a region with a long history of terrorism within its borders. This provides a valuable case study, and arguably a "hard case" given the likely presence of coping strategies in place among the general population to counter its effects. The relatively high frequency of low-level attacks can desensitise people. As terrorism violence is increasingly seen as normal, citizens are more likely to display resilience, leading to quicker return to baseline wellbeing levels despite the initial psychological impact of terrorism. Because of this dynamic, it is essential to consider the impact of terrorism in contexts with much lower incidence rates.

Second, the impact of terrorism can vary depending on individual characteristics, the nature and timing of the attack, and the location of the person affected. This study examines the average impact of terrorism on wellbeing and explores some of the key factors that mediate this relationship. We recognise the importance of further research to delve into other conditioning variables – and potentially interdependent factors – that shape the terrorism effects for the entire population or specific subgroups.

Third, we rely on self-reported subjective wellbeing, and one valuable direction would be to investigate the mental health consequences of terrorism using more objective measures, that do not rely on personal assessments, such as medical records or clinical diagnoses, as proposed by Sønderskov et al. (2021). This could provide a more accurate assessment of the impact of terrorism on mental health. Finally, it is crucial to evaluate the effectiveness of policy interventions designed to mitigate the negative consequences of terrorism. The efficacy of mental health support programs, community resilience strategies, or counter-terrorism measures in reducing the mental health burden caused by terrorist incidents is a fertile area of research. A more nuanced understanding of the impact of terrorism on wellbeing is crucial for policymakers, especially as managing the consequences of terrorism becomes increasingly central to public agendas, with wellbeing at the forefront of governmental concerns.

Acknowledgements

This research was funded by the Economic and Social Research Council (ESRC Grant number: ES/V002333/1). The work was also partially supported by the project "THE – Tuscany Health Ecosystem" (CUP: D63C22000400001), funded by the European Union – Next Generation EU program. We have benefited from comments and suggestions by the participants of the workshop on "The Economics of Beliefs, Culture and Institutions" at the University of Urbino, and research seminars at Newcastle University and the University of Florence.

6 References

Abadie, A. and Gardeazabal, J. (2003). The economic costs of conflict: a case study of the Basque Country. *American Economic Review*, 93(1):113–132.

Abramson, B., Boerma, J., and Tsyvinski, A. (2024). Macroeconomics of mental health. *NBER Working Papers, No. 32354*.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: assessing the effectiveness of Catholic schools. *Journal of Political Economy*, 113(1):151–184.

Arvanitidis, P., Economou, A., and Kollias, C. (2016). Terrorism's effects on social capital in European countries. *Public Choice*, 169:231–250.

Balcells, L. and Torrats-Espinosa, G. (2018). Using a natural experiment to estimate the electoral consequences of terrorist attacks. *Proceedings of the National Academy of Sciences*, 115(42):10624–10629.

Bauer, H. and Schulze, G. G. (2022). Terror and social cohesion. *Economics Letters*, 221:110922.

Blanchflower, D. G., Bryson, A., and Bell, D. N. (2024). The declining mental health of the young in the UK. *NBER Working Papers, No. 32879*.

Böhmelt, T., Bove, V., and Nussio, E. (2020). Can terrorism abroad influence migration attitudes at home? *American Journal of Political Science*, 64(3):437–451.

Bove, V., Efthyvoulou, G., and Pickard, H. (2022). Did terrorism affect voting in the Brexit referendum? *British Journal of Political Science*, 52(3):1133–1150.

Bove, V., Efthyvoulou, G., and Pickard, H. (2024). Are the effects of terrorism short-lived? *British Journal of Political Science*, 54(2):536–545.

Braithwaite, A. (2013). The logic of public fear in terrorism and counter-terrorism. *Journal of Police and Criminal Psychology*, 28:95–101.

Brewin, C. R. (2001). Cognitive and emotional reactions to traumatic events: implications for short-term intervention. *Advances in Mind-Body Medicine*.

Bryant, R. A. (2019). Post-traumatic stress disorder: a state-of-the-art review of evidence and challenges. *World Psychiatry*, 18(3):259–269.

Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4):1194–1225.

Clark, A. E., Doyle, O., and Stancanelli, E. (2020). The impact of terrorism on individual well-being: evidence from the Boston Marathon bombing. *The Economic Journal*, 130(631):2065–2104.

Cronin, A. K. (2002). Behind the curve: globalization and international terrorism. *International Security*, 27(3):30–58.

Dinesen, P. T. and Jæger, M. M. (2013). The effect of terror on institutional trust: new evidence from the 3/11 Madrid terrorist attack. *Political Psychology*, 34(6):917–926.

Dolan, P., Kavetsos, G., Krekel, C., Mavridis, D., Metcalfe, R., Senik, C., Szymanski, S., and Ziebarth, N. R. (2019). Quantifying the intangible impact of the Olympics using subjective well-being data. *Journal of Public Economics*, 177(1):104043.

Dustmann, C. and Fasani, F. (2016). The effect of local area crime on mental health. *The Economic Journal*, 126(593):978–1017.

Eckstein, Z. and Tsiddon, D. (2004). Macroeconomic consequences of terror: theory and the case of Israel. *Journal of Monetary Economics*, 51(5):971–1002.

Efthyvoulou, G., Pickard, H., and Bove, V. (2024). Terrorist violence and the fuzzy frontier: national and supranational identities in Britain. *The Journal of Law, Economics, and Organization*, DOI:10.1093/jleo/ewae003.

Epifanio, M., Giani, M., and Ivandic, R. (2023). Wait and see? Public opinion dynamics after terrorist attacks. *The Journal of Politics*, 85(3):843–859.

Falcó-Gimeno, A., Muñoz, J., and Pannico, R. (2023). Double-edged bullets: the conditional effect of terrorism on vote for the incumbent. *British Journal of Political Science*, 53(1):183–203.

Fisk, K., Merolla, J. L., and Ramos, J. M. (2019). Emotions, terrorist threat, and drones: anger drives support for drone strikes. *Journal of Conflict Resolution*, 63:976–1000.

Frey, B. S., Luechinger, S., and Stutzer, A. (2007). Calculating tragedy: assessing the costs of terrorism. *Journal of Economic Surveys*, 21(1):1–24.

Frijters, P., Clark, A. E., Krekel, C., and Layard, R. (2020). A happy choice: wellbeing as the goal of government. *Behavioural Public Policy*, 4(2):126–165.

Gaibulloev, K. and Sandler, T. (2019). What we have learned about terrorism since 9/11. *Journal of Economic Literature*, 57(2):275–328.

Getmansky, A. and Zeitzoff, T. (2014). Terrorism and voting: the effect of rocket threat on voting in Israeli elections. *American Political Science Review*, 108(3):588–604.

Godefroidt, A. (2023). How terrorism does (and does not) affect citizens' political attitudes: a meta-analysis. *American Journal of Political Science*, 67(1):22–38.

Goldberg, D. P., Gater, R., Sartorius, N., Ustun, T. B., Piccinelli, M., Gureje, O., and Rutter, C. (1997). The validity of two versions of the GHQ in the WHO study of mental illness in general health care. *Psychological Medicine*, 27(1):191–197.

Gould, E. D. and Klor, E. F. (2016). The long-run effect of 9/11: terrorism, backlash, and the assimilation of Muslim immigrants in the West. *The Economic Journal*, 126(597):2064–2114.

Graetz, B. (1991). Multidimensional properties of the general health questionnaire. *Social Psychiatry and Psychiatric Epidemiology*, 26:132–138.

Gray, D., Pickard, H., and Munford, L. (2021). Election outcomes and individual subjective wellbeing in Great Britain. *Economica*, 88(351):809–837.

Guo, S. and An, J. (2022). Does terrorism make people pessimistic? Evidence from a natural experiment. *Journal of Development Economics*, 155:102817.

Helliwell, J. F., Layard, R., and Sachs, J. D. (2023). The happiness agenda: the next 10 years. *World Happiness Report*, 2023:15.

Hole, A. R. and Ratcliffe, A. (2020). The impact of the London Bombings on the well-being of adolescent Muslims. *The Scandinavian Journal of Economics*, 122(4):1606–1639.

Kibris, A. (2011). Funerals and elections: the effects of terrorism on voting behavior in Turkey. *Journal of Conflict Resolution*, 55(2):220–247.

Kim, D. and Albert Kim, Y.-I. (2018). Mental health cost of terrorism: study of the Charlie Hebdo attack in Paris. *Health Economics*, 27(1):e1–e14.

Layard, R. (2021). Wellbeing as the goal of policy. *LSE Public Policy Review*, 2(2):1–8.

Layard, R. and Ward, G. (2020). *Can we be happier? Evidence and ethics*. Penguin UK.

Maguen, S., Papa, A., and Litz, B. T. (2008). Coping with the threat of terrorism: a review. *Anxiety, Stress, & Coping*, 21(1):15–35.

Metcalfe, R., Powdthavee, N., and Dolan, P. (2011). Destruction and distress: using a quasi-experiment to show the effects of the September 11 attacks on mental well-being in the United Kingdom. *The Economic Journal*, 121(550):F81–F103.

Mueller, J. and Stewart, M. G. (2014). Evaluating counterterrorism spending. *Journal of Economic Perspectives*, 28(3):237–248.

Muñoz, J., Falcó-Gimeno, A., and Hernández, E. (2020). Unexpected event during survey design: promise and pitfalls for causal inference. *Political Analysis*, 28(2):186–206.

Nussio, E., Bove, V., and Steele, B. (2019). The consequences of terrorism on migration attitudes across Europe. *Political Geography*, 75:102047.

ONS (2023). Office for National Statistics, Annual survey of hours and earnings (ASHE): 1997 to 2015 selected estimates. Accessed: 2024-08-07.

Pennebaker, J. W. and Harber, K. D. (1993). A social stage model of collective coping: the Loma Prieta earthquake and the Persian Gulf War. *Journal of Social issues*, 49(4):125–145.

Powdthavee, N., Plagnol, A. C., Frijters, P., and Clark, A. E. (2019). Who got the Brexit blues? The effect of Brexit on subjective wellbeing in the UK. *Economica*, 86(343):471–94.

Rauch, S. A., Kim, H. M., Acierno, R., Ragin, C., Wangelin, B., Blitch, K., Muzzy, W., Hart, S., Zivin, K., and Cigrang, J. (2022). Improving function through primary care treatment of PTSD: The IMPACT study protocol. *Contemporary Clinical Trials*, 120:106881.

Romanov, D., Zussman, A., and Zussman, N. (2012). Does terrorism demoralize? Evidence from Israel. *Economica*, 79(313):183–198.

Sacks, D. W., Stevenson, B., and Wolfers, J. (2010). Subjective well-being, income, economic development and growth. *NBER Working Papers, No. 16441*.

Shayo, M. and Zussman, A. (2011). Judicial ingroup bias in the shadow of terrorism. *The Quarterly Journal of Economics*, 126(3):1447–1484.

Smith, K. V., Mansfield, C., and Clayton, L. (2008). Valuing a homeland security policy: countermeasures for the threats from shoulder mounted missiles. *NBER Working Papers, No. 14325*.

Sønderskov, K. M., Dinesen, P. T., Hansen, B. T., Østergaard, S. D., and Danckert, B. (2021). Terrorism in the country of origin is linked to deterioration in the mental health of refugees. *Nature Human Behaviour*, 5(11):1555–1561.

Vlandas, T. and Halikiopoulou, D. (2024). Jihadist terrorist attacks and far-right party preferences: an "Unexpected Event During Survey Design"' in four European countries. *Perspectives on Politics*, DOI:10.1017/S1537592723002980.

Zagefka, H. (2018). It could have been me: proximity motivates disaster giving. *International Journal of Nonprofit and Voluntary Sector Marketing*, 23(1):e1587.

Table 1: Summary statistics of key variables.

	Sample 1					Sample 2				
	Mean	Std. Dev.	Min.	Max.	Obs.	Mean	Std. Dev.	Min.	Max.	Obs.
Life satisfaction	5.18	1.42	1	7.00	1,032,722					
Mental distress						11.19	5.44	0	36.00	1,298,976
Social dysfunction						6.51	2.30	0	18.00	1,298,976
Anxiety and depression						3.54	2.56	0	12.00	1,298,976
Confidence loss						1.14	1.35	0	6.00	1,298,976
Exposure	-0.04	0.97	-1.91	7.34	1,032,722	-0.03	0.97	-1.91	7.34	1,298,976
Geographic distance (kms)	229.22	155.64	0.10	1091.10	1,032,722	226.78	154.21	0.10	1091.10	1,298,976

Table 2: Terrorism exposure and life satisfaction: main results.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lagged value				0.006	0.006	-0.001
				(0.004)	(0.004)	(0.004)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.603	0.604	0.607	0.603	0.604	0.607
No. of individuals	53,511	53,511	53,511	53,511	53,511	53,511
No. of observations	1,032,722	1,032,722	1,032,722	1,032,722	1,032,722	1,032,722

Notes: Lagged value is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: Terrorism exposure and life satisfaction: time proximity to attacks.

	Life satisfaction					
	Attacks $>$ 30 days			Attacks $\leq$ 30 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.002	-0.003	-0.002	-0.012**	-0.012**	-0.011**
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Lagged value	0.008**	0.008**	0.002	0.001	0.001	-0.005
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.608	0.609	0.612	0.739	0.740	0.742
No. of individuals	53,102	53,102	53,102	21,028	21,028	21,028
No. of observations	950,476	950,476	950,476	67,941	67,941	67,941

Notes: Lagged value is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: Terrorism exposure and life satisfaction: initial conditions.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.001	-0.011	-0.008	-0.001	-0.011	-0.008
	(0.016)	(0.007)	(0.006)	(0.016)	(0.007)	(0.006)
Lagged value				-0.005	-0.005	-0.005
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [≤ 6]	-0.012			-0.012		
	(0.017)			(0.017)		
Exposure × Initial value [≤ 5]		-0.002			-0.002	
		(0.011)			(0.011)	
Exposure × Initial value [≤ 4]			-0.013			-0.013
			(0.014)			(0.014)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.742	0.742	0.742	0.742	0.742	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. *Initial value* [$\leq$ X] captures individuals with initial value of life satisfaction equal to X or less (on the 1-7 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Terrorism exposure and life satisfaction: falsification tests.

	Lagged life satisfaction			Financial wellbeing		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.004	-0.004	-0.003	-0.003	-0.003	-0.003
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave $\times$ Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.728	0.729	0.731	0.806	0.807	0.813
No. of individuals	21,028	21,028	21,028	21,001	21,001	21,001
No. of observations	67,941	67,941	67,941	67,844	67,844	67,844

Notes: The results are based on the 30-day time window to terrorism exposure. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Monetary equivalent of wellbeing loss

WTP (£)	Area code	Area name	Adult population (thousands)	Average no. of attacks per year	Adjusted WTP (£)	Aggregate WTP (£) (thousands)	Adjust. Aggregate WTP (£) (thousands)
	E08000025	Birmingham	905.3	0.16	12.56	71,085	11,374
	E08000032	Bradford	429.4	0.48	37.69	33,717	16,184
	E06000023	Bristol, City of	394.2	0.16	12.56	30,953	4,952
	W06000015	Cardiff	300.3	0.16	12.56	23,580	3,773
	E08000026	Coventry	280,9	0.16	12.56	22,057	3,529
	E06000015	Derby	212.3	0.44	34.55	16,670	7,335
	E13000001	Inner London	2,854.5	1.72	135.06	224,138	385,517
	E06000010	Kingston upon Hull, City of	216.9	0.20	15.70	1,7031	3,406
	E08000035	Leeds	667.4	0.44	34.55	52,404	23,058
	E06000016	Leicester	295.9	0.16	12.56	23,234	3,717
78.52	E08000012	Liverpool	407.8	0.44	34.55	32,021	14,089
	E08000003	Manchester	444.7	0.48	37.69	34,918	16,761
	E08000021	Newcastle upon Tyne	251.6	0.04	3.14	19,756	790
	E06000018	Nottingham	267.9	0.36	28.27	21,036	7,572
	E06000026	Plymouth	221.3	0.04	3.14	17,377	695
	E08000019	Sheffield	462.2	0.52	40.83	36,292	18,872
	E06000045	Southampton	206.9	0.20	15.70	16,246	3,249
	E06000021	Stoke-on-Trent	208.9	0.56	43.97	16,403	9,186
	W06000011	Swansea	200.40	0.12	9.42	15,736	1,888
	E08000031	Wolverhampton	211.9	0.16	12.56	16,639	2,662

Notes: Population figures are from the 2021 Census.

Table 7: Terrorism exposure and mental distress: main results.

Panel A	**Mental distress**					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.009*	0.008	0.008	0.008	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Lagged value				0.083***	0.083***	0.073***
				(0.004)	(0.004)	(0.004)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.604	0.605	0.611	0.607	0.608	0.613
No. of individuals	56,747	56,747	56,747	56,747	56,747	56,747
No. of observations	1,298,976	1,298,976	1,298,976	1,298,976	1,298,976	1,298,976
Panel B	**Mental distress**					
	Attacks $>$ 30 days			Attacks $\leq$ 30 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.006	0.006	0.006	0.019	0.020	0.017
	(0.005)	(0.005)	(0.005)	(0.021)	(0.021)	(0.021)
Lagged value	0.086***	0.086***	0.076***	0.078***	0.078***	0.068***
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.609	0.610	0.615	0.757	0.758	0.762
No. of individuals	56,350	56,350	56,350	24,060	24,059	24,059
No. of observations	1,203,781	1,203,779	1,203,779	80,263	80,261	80,261

Notes: Lagged value is the individual's mental distress score in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Terrorism exposure and mental distress: initial conditions.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.059**	-0.029	-0.015	-0.060**	-0.029	-0.016
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.067***	0.067***	0.067***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.123***			0.120***		
	(0.038)			(0.038)		
Exposure × Initial value [> 10]		0.108***			0.103**	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.127**			0.122**
			(0.052)			(0.052)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

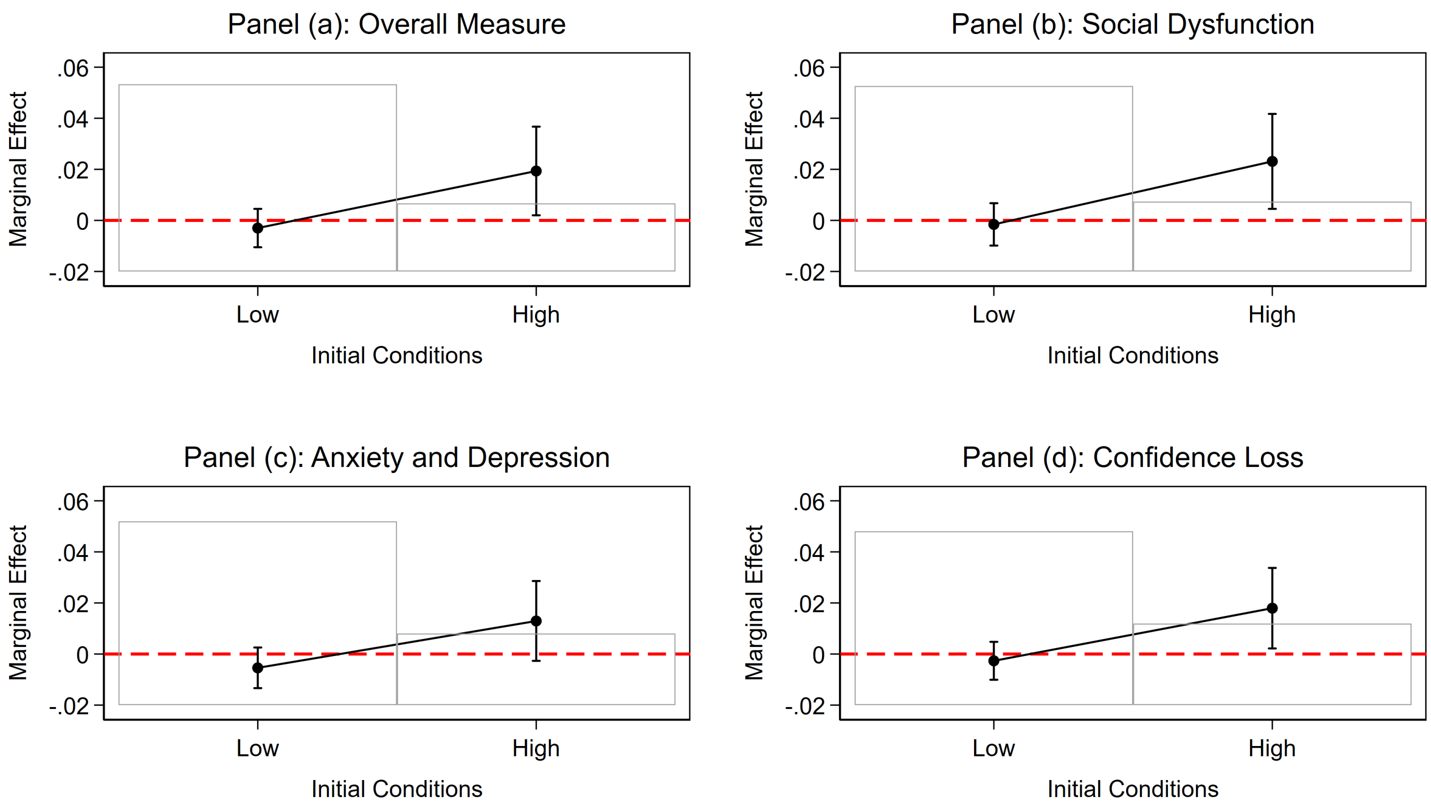
Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9: Terrorism exposure and mental distress: falsification tests.

	Lagged mental distress			Physical health		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.002	0.002	0.015	0.046	0.038	0.017
	(0.027)	(0.023)	(0.021)	(0.047)	(0.040)	(0.035)
Exposure × Initial value [> 8]	0.049			-0.070		
	(0.037)			(0.060)		
Exposure × Initial value [> 10]		0.070*			-0.081	
		(0.041)			(0.060)	
Exposure × Initial value [> 12]			0.069			-0.055
			(0.051)			(0.070)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.752	0.752	0.752	0.879	0.879	0.879
No. of individuals	24,059	24,059	24,059	19,257	19,257	19,257
No. of observations	80,261	80,261	80,261	61,510	61,510	61,510

Notes: The results are based on the 30-day time window to terrorism exposure. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 1: Terrorism exposure and mental distress: decomposing the effects.



Notes: This figure shows the marginal effects of exposure on the overall measure and the three sub-measures of *Mental distress* at values 0 and 1 of initial conditions. All measures have been standardised. 'Low' (value 0) refers to individuals at the two lowest tertiles of the initial value of the corresponding measure. 'High' (value 1) refers to individuals at the highest tertile of the initial value of the corresponding measure. Vertical lines signify 95% confidence intervals. The underlying bar charts are histograms of the initial value, showing the relative frequency of observations within each bin.

Beyond the Headlines:
The intangible costs of terrorism

Supplementary Information (SI) Appendix

For Online Publication

Harry Pickard

Newcastle University, UK

Vincenzo Bove

IMT School for Advanced Studies Lucca and and CAGE (Competitive Advantage in the Global Economy), University of Warwick

Georgios Efthyvoulou

University of Sheffield, UK

Contents

A Background and Descriptives

A.1 Background information

Figure A.1.1 maps the 97 casualty-causing terrorist incidents in our sample, covering the period 1992–2020. The left panel shows the spatial distribution across Great Britain and the right panel shows the attacks that occurred within Greater London. The graph demonstrates that, while a large number of attacks took place in London, terrorist activity was spread throughout the entire country. It also indicates clusters of incidents in major urban centers as well as occurrences in more remote locations. Out of the 97 sampled attacks, the vast majority (90) occurred in England, while Scotland and Wales experienced 4 and 3 incidents, respectively. The detailed London inset reveals the dense concentration of incidents in the capital, highlighting its status as a primary target.

Figure A.2 presents the frequency of all casualty-causing incidents (in black) and the subset of deadly attacks (in red) across the sampled years. The time series illustrates a surge in incidents in the early 1990s, followed by a decline in the mid-late 1990s, and large variability in the 2000s. Years marked by high levels of violence, such as 2017 and 2020, are also clearly indicated. Overall, the pattern demonstrates that terrorism has remained a consistent threat in Great Britain with varying intensity over the three-decade period of study. Out of the 97 incidents in the sample, 28 resulted in at least one fatality, with death tolls ranging from 1 to 27 (a median of 1.5). Additionally, 89 incidents led to at least one injury, with the number of injuries ranging from 1 to 340 (a median of 2). The type (and number) of victims is a commonly used measure of the severity of an incident. It can also serve as a proxy for the event's media coverage, as the media tend to give more attention to lethal attacks and those viewed as major threats to the public (Bove, Efthyvoulou and Pickard, 2024; Efthyvoulou, Pickard and Bove, 2024).[1]

[1]Obtaining reliable and comparable data on media coverage since the early 1990s presents a considerable

Given the diverse nature of terrorist activity in Great Britain, we now provide descriptive information about some of the sampled attacks.

- June 15, 1996 – Corporation Street, Manchester: The IRA detonated a truck bomb containing 3,000 pounds of explosives outside the Arndale shopping centre. Thanks to warning calls from the IRA that prompted an evacuation, no deaths occurred despite the massive explosion. The incident resulted in approximately 200 injuries, primarily from flying glass and debris.

- April 17, 1999 – Brixton, London: A nail bomb targeting the Afro-Caribbean community was detonated by David Copeland, who was later identified as a "self-confessed homophobic Nazi." This was the first of three bombings he would carry out in London that April. While Combat 18 and White Wolves claimed responsibility, Copeland had no confirmed affiliation with either group. The attack resulted in 48 injuries with no fatalities.

- June 16, 1999 - Whitely Bay, North Tyneside: A suspected Irish Republican Army attack where an unidentified gunman shot a former special branch agent. The incident resulted in 1 injury.

- July 7, 2005 – London Underground: A suicide bombing occurred on the London Underground between Russell Square and Kings Cross Stations. The attack was linked to al-Qaida through documents discovered by German authorities in 2011. The incident resulted in 27 deaths and 340 injuries.

- July 7, 2005 – Tavistock Square, London: A suicide bombing targeted a No. 30 Dennis Trident 2 double-decker bus. Like the Underground bombing on the same day,

challenge due to changes in data sources, media formats, and accessibility over time. Digital transformations from the 2000s onwards further complicate data continuity.

al-Qaida's involvement was confirmed through documents found by German authorities in 2011. The attack resulted in 14 deaths and 110 injuries.

- June 30, 2007 – Glasgow Airport, Scotland: A vehicle-borne incendiary attack where two men reportedly linked to Al-Qaida in Iraq (identified as Bilal Abdulla, a medical doctor, and Kafeel Ahmed, an aeronautical engineer) drove a gasoline-laden Jeep Cherokee into the airport terminal. Ahmed later died from burns sustained in the attack. The incident resulted in 2 injuries and 1 death.

- June 16, 2016 – Birstall, England: Labour MP Jo Cox was fatally attacked by Tommy Mair, a neo-Nazi supporter, who both shot and stabbed her. The attack was politically motivated, with Mair shouting "put Britain first" during the assault and later declaring in court "Death to traitors, freedom for Britain." Cox had been a supporter of Britain remaining in the European Union. The incident resulted in 1 death and 1 injury.

- May 22, 2017 – Manchester Arena: A suicide bombing targeted concertgoers following an Ariana Grande performance. The attacker was identified as Salman Abedi, and the Islamic State of Iraq and the Levant (ISIL) claimed responsibility, stating it was retaliation for "transgressions against the lands of the Muslims." The attack resulted in 23 deaths and 119 injuries.

- June 3, 2017 – London Bridge & Borough Market: A combined vehicle-ramming and stabbing attack was carried out by three assailants wearing fake suicide vests. The attackers (identified as Khuram Butt, Rachid Redouane, and Youssef Zaghba) first drove a van into pedestrians on London Bridge, then proceeded to stab civilians in nearby Borough Market establishments. The incident resulted in 11 deaths and 48 injuries. The attackers were killed by security forces.

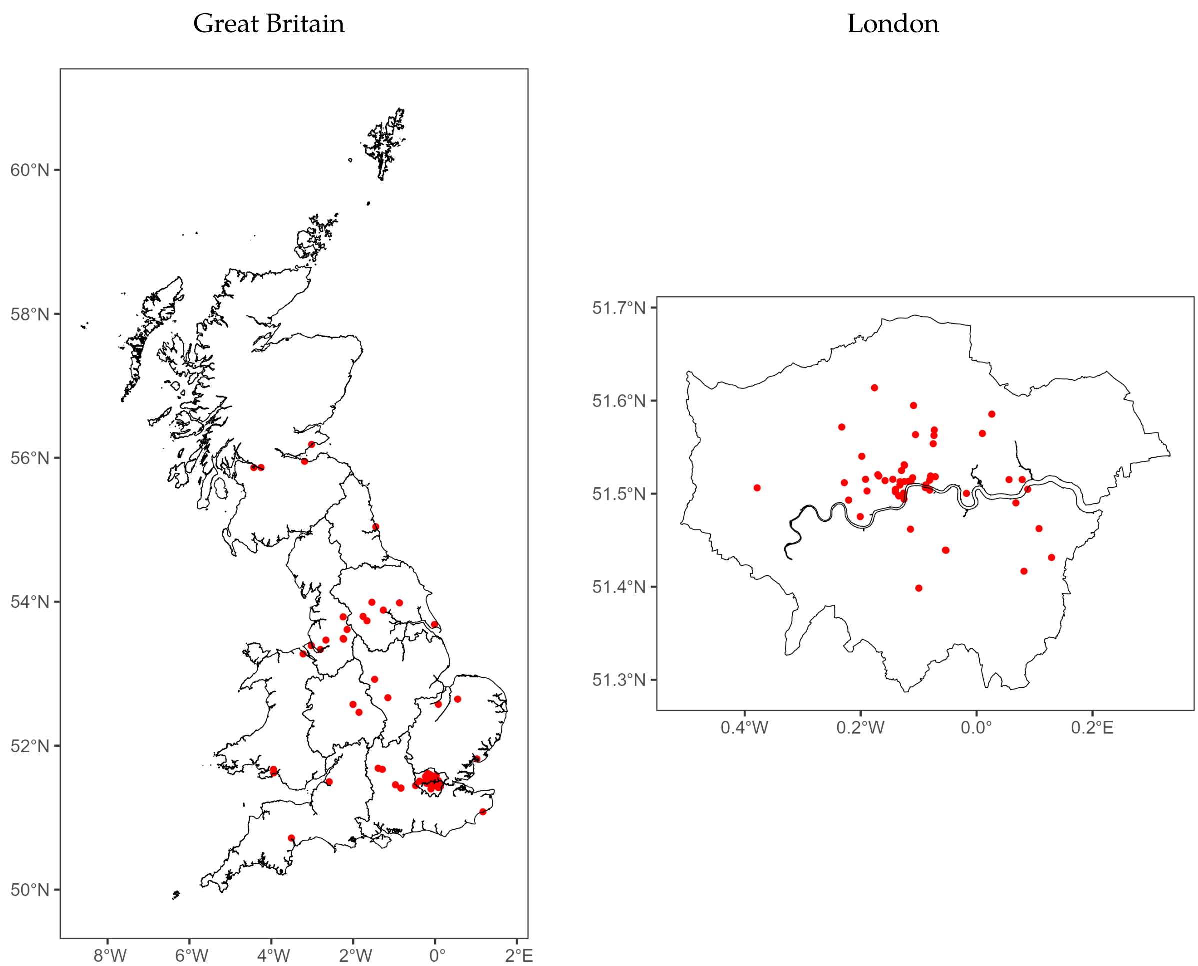
- September 15, 2017 – Parsons Green Station, London: An explosive device detonated on a London Underground train. The attacker was identified as Ahmed Hassan, who initially claimed to have been "trained to kill" by ISIL but later retracted this statement. While ISIL claimed responsibility for the attack, Hassan's connection to the group remained unclear. The incident resulted in 69 injuries with no fatalities.

- November 29, 2019 - London Bridge: A knife attack occurred at a University of Cambridge "Learning Together" conference held at Fishmongers' Hall. The assailant, wearing a fake explosive vest, was identified as a Jihadi-inspired extremist. The incident resulted in 3 deaths and 3 injuries.

- February 2, 2020 – Streatham, London: A knife attack was carried out by Sudesh Amman, who wore a fake explosive vest and had previously pledged allegiance to ISIL. After the incident, ISIL claimed the attacker was one of their "soldiers" responding to calls to target civilians in coalition countries. The assailant was killed by police during the response. The attack resulted in 3 injuries and 1 death.

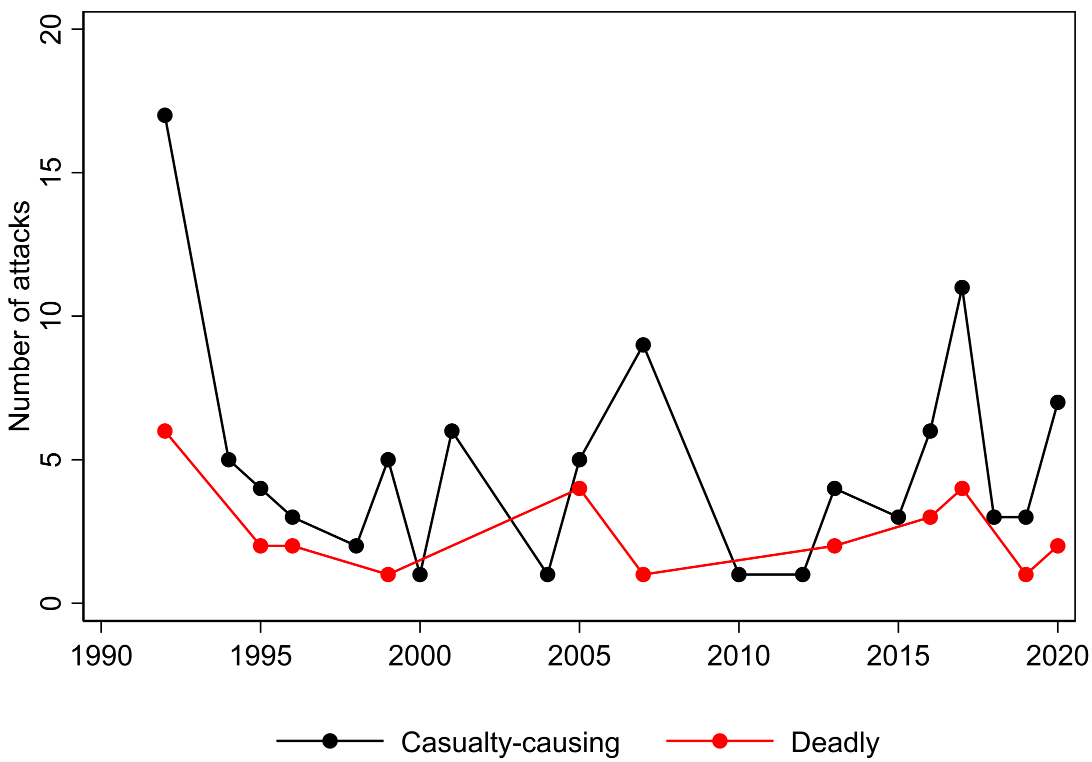
- June 20, 2020 – Forbury Gardens, Reading: A knife attack was carried out by Khairi Saadallah, a Libyan asylum recipient. Saadallah admitted to carrying out the attack, which resulted in 3 deaths and 3 injuries.

Figure A.1.1: Terrorist attacks across space.



Notes: The figure shows the geographic distribution of the terrorist attacks used in our analysis.

Figure A.1.2: Terrorist attacks over time.



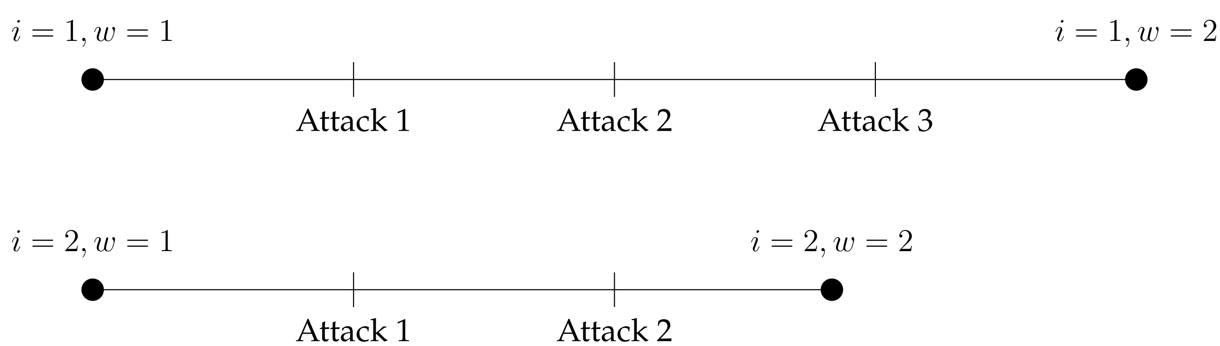
Notes: The figure shows the temporal distribution of terrorist attacks from 1992 to 2020. It plots two sets of data: all recorded terrorist attacks during this period and a subset of these attacks that resulted in at least one fatality.

A.2 Data construction illustration

Below is a hypothetical example illustrating the process of creating the individual-wave-attack level dataset. As explained in the paper, we amalgamate an individual-wave panel with terrorist incidents using the interview dates from BHPS-UKHLS and the timing of attacks. The timelines presented below depict two hypothetical individuals and the corresponding attacks.

In the upper timeline, individual (i) 1 completes the survey wave (w) 1 and is potentially exposed to three attacks (a) before completing survey wave 2. Therefore, individual 1 in wave 2 will be assigned to all three attacks, resulting in three rows in our dataset $\{i, w, a = 1, 2, 1; 1, 2, 2; 1, 2, 3\}$. In the lower timeline, individual 2 undergoes wave 2 earlier than individual 1. Due to the shorter time frame, individual 2 is exposed to only two attacks. Consequently, individual 2 in wave 2 will be assigned to two attacks, leading to two rows in our dataset $\{i, w, a = 2, 2, 1; 2, 2, 2\}$.

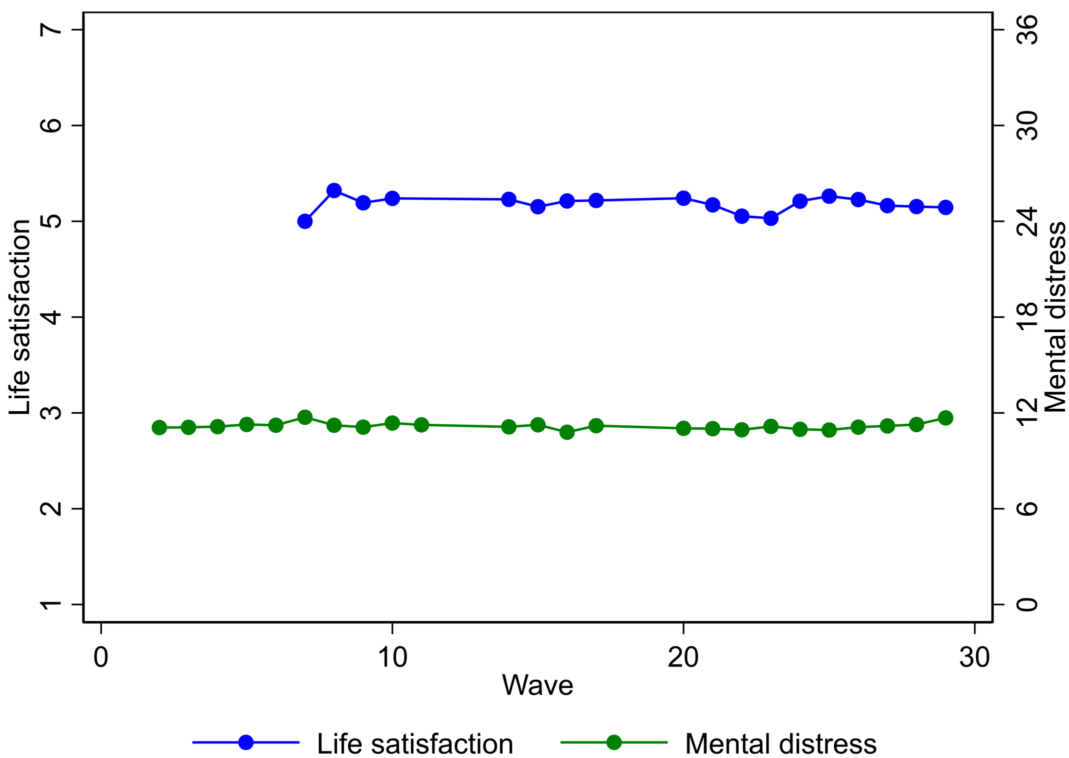
Figure A.2: An example of the data construction timelines.



A.3 Evolution of wellbeing measures

Figure A.3 shows the average value of the two outcome variables across the BHPS-UKHLS waves used in our analysis.

Figure A.3: Life satisfaction and mental distress.



Notes: The figure illustrates the evolution of each measure of well-being, as indicated on each y-axis, across the BHPS-UKHLS waves used in our analysis.

A.4 Summary statistics

Table A.4 provides summary statistics for all variables used in our analysis.

Table A.4: Summary statistics.

	Sample 1					Sample 2				
	Mean	Std. Dev.	Min.	Max.	Obs.	Mean	Std. Dev.	Min.	Max.	Obs.
Life satisfaction	5.18	1.42	1	7.00	1,032,722					
Financial wellbeing	3.95	0.96	1	5.00	1,031,338					
Mental distress						11.19	5.44	0	36.00	1,298,976
Mental distress (0-12)						1.81	3.00	0	12.00	1,298,965
Social dysfunction						6.51	2.30	0	18.00	1,298,976
Anxiety and depression						3.54	2.56	0	12.00	1,298,976
Confidence loss						1.14	1.35	0	6.00	1,298,976
Physical health						49.28	11.09	4.48	75.48	804,161
Exposure	-0.04	0.97	-1.91	7.34	1,032,722	-0.03	0.97	-1.91	7.34	1,298,976
Geographic distance (kms)	229.22	155.64	0.10	1091.10	1,032,722	226.78	154.21	0.10	1091.10	1,298,976
Exposure (deciles)	5.50	2.87	1	10.00	1,032,722	5.50	2.87	1	10.00	1,298,976
Proximity to London	-0.05	0.96	-1.71	4.17	1,032,722	-0.05	0.95	-1.71	4.17	1,298,976
Deadly attack	0.30	0.46	0	1	1,032,722	0.30	0.46	0	1	1,298,976
Female	0.56	0.50	0	1	1,032,722	0.55	0.50	0	1	1,298,976
White British	0.82	0.38	0	1	1,032,722	0.85	0.36	0	1	1,298,976
Age	50.43	17.92	16.00	103.00	1,032,722	49.53	17.97	16.00	103.00	1,298,976
Age squared	2864.59	1844.62	256.00	10609.00	1,032,722	2776.25	1838.32	256.00	10609.00	1,298,976
Income (dec): Poorest	0.10	0.29	0	1	1,032,722	0.10	0.29	0	1	1,298,976
Income (dec): 2	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 3	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 4	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 5	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 6	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 7	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 8	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): 9	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Income (dec): Richest	0.10	0.30	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Job status: Self-employed	0.08	0.27	0	1	1,032,722	0.08	0.27	0	1	1,298,976
Job status: Employed	0.49	0.50	0	1	1,032,722	0.49	0.50	0	1	1,298,976
Job status: Unemployed	0.03	0.18	0	1	1,032,722	0.03	0.18	0	1	1,298,976
Job status: Retired	0.27	0.44	0	1	1,032,722	0.25	0.43	0	1	1,298,976
Job status: On maternity leave	0	0.07	0	1	1,032,722	0	0.07	0	1	1,298,976
Job status: Family care	0.05	0.21	0	1	1,032,722	0.06	0.23	0	1	1,298,976
Job status: Full-time student	0.04	0.20	0	1	1,032,722	0.04	0.20	0	1	1,298,976
Job status: Long-term sick or disabled	0.03	0.18	0	1	1,032,722	0.03	0.18	0	1	1,298,976
Job status: Govt. training scheme	0	0.02	0	1	1,032,722	0	0.03	0	1	1,298,976
Job status: Other	0.01	0.09	0	1	1,032,722	0.01	0.08	0	1	1,298,976
Highest qualification: Degree	0.25	0.43	0	1	1,032,722	0.22	0.41	0	1	1,298,976
Highest qualification: other higher degree	0.12	0.33	0	1	1,032,722	0.11	0.32	0	1	1,298,976
Highest qualification: A-level	0.21	0.41	0	1	1,032,722	0.21	0.41	0	1	1,298,976
Highest qualification: GCSE	0.21	0.40	0	1	1,032,722	0.21	0.41	0	1	1,298,976
Highest qualification: Other qualification	0.09	0.29	0	1	1,032,722	0.10	0.30	0	1	1,298,976
Highest qualification: No qualification	0.12	0.32	0	1	1,032,722	0.15	0.36	0	1	1,298,976
Marital status: Married civil partnership or living as couple	0.67	0.47	0	1	1,032,722	0.67	0.47	0	1	1,298,976
Marital status: Separated divorced or widowed	0.15	0.35	0	1	1,032,722	0.15	0.35	0	1	1,298,976
Household size	2.81	1.41	1	15.00	1,032,722	2.82	1.40	1	15.00	1,298,976
Having children	0.26	0.44	0	1	1,032,722	0.27	0.45	0	1	1,298,976

A.5 Supporting analyses

Benchmarking exercises

In Table A.5.1, we provide a series of estimates of the effect of major personal life events on life satisfaction, which we use to benchmark our terrorism exposure effect against. Using the full panel version of the BHPS-UKHLS dataset, we define a series of dummy variables that take value 1 in the first wave that there is a change in an individual's circumstances. We do so to capture the immediate, short-run effect of each event. The events we examine are having a new baby, becoming newly unemployed, becoming newly long-term sick/disabled, getting newly married and becoming newly widowed. The estimates suggest, for instance, that having a new baby increases life satisfaction by 0.174 units and that becoming newly long-term sick or disabled reduces life satisfaction by 0.404 units on average. These values are equivalent to about 12% and 29% of the variable's standard deviation, respectively.

Using a binary measure of exposure

In Table A.5.2, we replicate our main analysis for life satisfaction using a binary version of the exposure measure that equals 1 when an individual resides within 100 kms of an attack that occurred in the last 30 days. We do this exercise because it helps the interpretation of our WTP calculations in Section 3.4. The estimates suggest that being within this geographic area reduces life satisfaction by 0.019 units on the 1-7 scale.

Table A.5.1: Life satisfaction and major personal life events.

	Life satisfaction	
	(1)	(2)
Panel A		
New baby	0.175***	0.174***
	(0.011)	(0.011)
R-squared	0.490	0.491
No. of individuals	62,018	62,018
No. of observations	447,983	447,983
Panel B		
Newly unemployed	-0.319***	-0.296***
	(0.021)	(0.021)
R-squared	0.491	0.491
No. of individuals	62,018	62,018
No. of observations	447,983	447,983
Panel C		
Newly long-term sick/disabled	-0.411***	-0.404***
	(0.023)	(0.023)
R-squared	0.491	0.491
No. of individuals	62,018	62,018
No. of observations	447,983	447,983
Panel D		
Newly married	0.152***	0.151***
	(0.014)	(0.014)
R-squared	0.490	0.491
No. of individuals	62,018	62,018
No. of observations	447,983	447,983
Panel E		
Newly widowed	-0.316***	-0.305***
	(0.029)	(0.029)
R-squared	0.490	0.491
No. of individuals	62,018	62,018
No. of observations	447,983	447,983
Individual FEs	✓	✓
Wave FEs	✓	✓
Controls		✓
Life satisfaction mean	5.184	5.184
Life satisfaction S.D.	1.413	1.413
Life satisfaction Within S.D.	1.011	1.011

Notes: Controls are age, age squared, a set of highest qualification dummies and a set income decicle dummies. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.5.2: Terrorism exposure and life satisfaction:
Using a binary indicator of exposure.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure ($\leq$ 100 km)	-0.022*	-0.021*	-0.019*	-0.022*	-0.021*	-0.019*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lagged value				0.001	0.001	-0.005
				(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B Robustness Tests and Further Insights: Life Satisfaction

B.1 Controlling for attacked MSOAs

This section examines whether the terrorism effect on life satisfaction is primarily driven by the attacked localities. To do that, we augment Eq. (1) with a binary indicator capturing whether attack a took place within the boundaries of individual i's MSOA of residence in wave w. The results are presented in Table B.1. The estimates for residing within the attacked MSOA are negatively signed and very large in magnitude, but fail to reach statistical significance. More importantly, the estimates of *Exposure* remain identical to those reported in Table 3 (for recent attacks) and continue to be statistically significant at the 5%. The latter supports the idea that terrorism causes spillover effects on individuals in neighbouring areas, and helps address concerns about omitted heterogeneity; specifically, the presence of unobserved time-varying factors that could affect both the likelihood of an MSOA experiencing attacks and its residents' wellbeing losses.

Table B.1: Terrorism exposure and life satisfaction: Controlling for attacked MSOAs.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.012**	-0.012**	-0.011**	-0.012**	-0.012**	-0.011**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged value				0.001	0.001	-0.005
				(0.009)	(0.009)	(0.009)
Attacked MSOA	-0.343	-0.371	-0.374	-0.342	-0.370	-0.378
	(0.472)	(0.456)	(0.458)	(0.472)	(0.457)	(0.457)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.2 Controlling for proximity to London

Since London has the highest concentration of terrorist attacks in our sample, the geographic proximity to the UK's capital city could confound the effect of our measure of exposure. To address this, we extend our baseline specification by controlling for the proximity between an individual's MSOA and central London (reverse of the log of distance, standardised). As shown in Table B.2, the estimates of *Exposure* are virtually unchanged. This rules out the possibility that our results are merely an artifact of moving closer to London,[2] or unobserved time-varying factors associated with proximity to the UKs' economic and political centre.

Table B.2: Terrorism exposure and life satisfaction: Controlling for proximity to London.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.012**	-0.012**	-0.011**	-0.012**	-0.012**	-0.011**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged value				0.001	0.001	-0.005
				(0.009)	(0.009)	(0.009)
Proximity to London	-0.031	-0.030	-0.017	-0.031	-0.030	-0.017
	(0.063)	(0.063)	(0.064)	(0.062)	(0.063)	(0.064)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

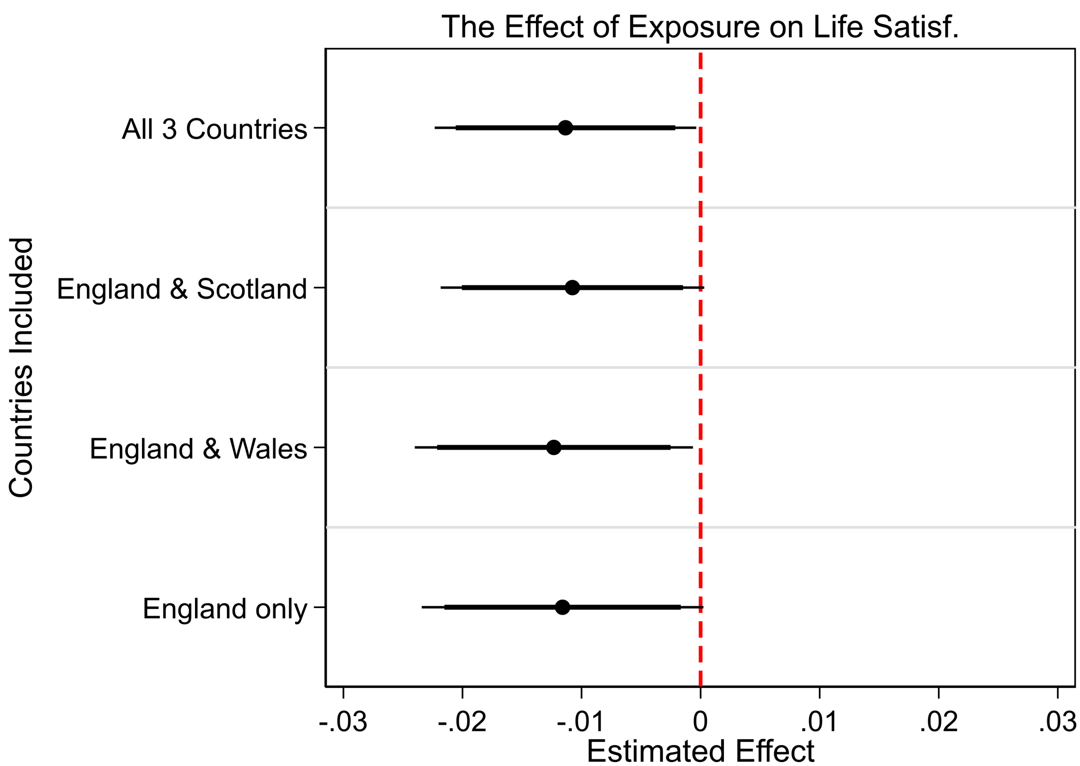
Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[2] Note that a small number of respondents appear in two different MSOAs, with at least two wave-on-wave observations in each MSOA (which correspond to the current and lagged value of the outcome variable). This can explain why the estimate of *Proximity to London* is not absorbed by the individual fixed effects.

B.3 Excluding Scotland and Wales

In this section, we check whether our results persist when we drop individuals living in Scotland and Wales, where terrorist incidents occur less frequently and wellbeing may be influenced by idiosyncratic country-specific factors. In Figure B.3, we compare the estimates for the full sample (i.e., all three countries in Great Britain) with those obtained when we exclude Scotland and Wales, first one-by-one and then together. Overall, the average impact of exposure to terrorism is very similar across the four samples. It should be stressed that we are unable to run the same regressions separately for Scotland and Wales due to the small sample size. In addition, focusing on relatively small geographic areas within Great Britain reduces significantly the variation in exposure (i.e., geographic proximity to terrorism) used for identification.

Figure B.3: Terrorism exposure and life satisfaction:
Excluding Scotland and Wales.



Notes: The estimates are based on the full model specification (with the three sets of fixed effects, controls, and lagged value). Thick (thin) lines denote statistical significance at the 90% (95%) level.

B.4 Testing for attrition

In this section, we assess to what extent our results might be affected by attrition. A potential concern is that individuals who are repeatedly exposed to terrorism may decide to leave the survey. If this happens, our sample would disproportionately consist of individuals who are less affected by terrorist events, leading to an underestimation of the true impact of terrorism on life satisfaction. To mitigate this concern, we restrict the sample to include only respondents who participated in at least five waves of the survey, and replicate the same analysis. As shown in Table B.4, despite the decrease in the number of individuals by about 22%, our inferences do not change. In fact, the estimates are now slightly larger, which allows us to rule out the possibility that our results are driven by individuals with short survey participation.

Table B.4: Terrorism exposure and life satisfaction:
Keeping respondents who participated in at least five survey waves

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.016**	-0.015**	-0.014**	-0.016**	-0.015**	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged value				0.011	0.011	0.005
				(0.010)	(0.010)	(0.010)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave $\times$ Week FEs		✓	✓			✓
Controls			✓			✓
R-squared	0.709	0.710	0.712	0.709	0.710	0.712
No. of individuals	16,447	16,447	16,447	16,447	16,447	16,447
No. of observations	55,142	55,142	55,142	55,142	55,142	55,142

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.5 Closest-attack-between waves strategy

In our main analysis, we assign multiple attacks to each respondent in each wave. An alternative approach is to employ a closest-attack-between-waves strategy. In other words, we can assume that each individual is exposed to only one attack between two waves, the closest one geographically. The drawback of this approach is that it introduces some bias from not accounting for the impact of multiple nearby incidents, which could also vary in their severity. For instance, a deadly attack in a neighbouring MSOA might have a greater impact on wellbeing than a non-deadly attack in the respondent's own MSOA. As shown in Table B.5, our results are robust to using this strategy and thus do not depend on how we decide to structure the data.

Table B.5: Terrorism exposure and life satisfaction:
Closest-attack-between-waves strategy.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.018**	-0.017*	-0.017*	-0.018**	-0.017*	-0.017*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Lagged value				0.000	-0.001	-0.007
				(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.657	0.659	0.662	0.657	0.659	0.662
No. of individuals	16,667	16,667	16,667	16,667	16,667	16,667
No. of observations	42,667	42,667	42,667	42,667	42,667	42,667

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B.6 Alternative specifications of temporal fixed effects

In this section, we assess robustness to different specifications of temporal fixed effects. Specifically, we consider two modifications of the baseline model. In Table B.6.1, we replace wave $\times$ week fixed effects ϕ_{wt} with day fixed effects to capture any omitted heterogeneity associated with the exact dates of the interviews. In Table B.6.2, we augment the model with time distance fixed effects. This allows us to control for unobserved factors related to the time distance (measured in days) between attacks and interviews. In both cases, the results remain essentially unchanged when compared to those presented in Table 3.

Table B.6.1: Terrorism exposure and life satisfaction:
Using day fixed effects.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.012**	-0.013**	-0.011**	-0.012**	-0.013**	-0.011**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Lagged value				0.001	0.002	-0.004
				(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Day FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.751	0.753	0.739	0.751	0.753
No. of individuals	21,028	21,021	21,021	21,028	21,021	21,021
No. of observations	67,941	67,921	67,921	67,941	67,921	67,921

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.6.2: Terrorism exposure and life satisfaction:
Including time distance fixed effects.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.012**	-0.012**	-0.011**	-0.012**	-0.012**	-0.011**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged value				0.002	0.001	-0.005
				(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Time distance FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.7 Alternative error clustering

In our main analysis, we cluster standard errors at the individual level. Here, we check robustness to using clustering at the MSOA level, which groups individuals according to their area of residence. The results, presented in Table B.7, do not change our inferences. While clustering at the MSOA level yields somewhat larger standard errors, the estimates of *Exposure* continue to be statistically significant at conventional levels.

Table B.7: Terrorism exposure and life satisfaction:
Alternative error clustering.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.012*	-0.012*	-0.011*	-0.012*	-0.012*	-0.011*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lagged value				0.001	0.001	-0.005
				(0.011)	(0.011)	(0.011)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of MSOAs	5,785	5,785	5,785	5,785	5,785	5,785
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.8 Alternative geographic proximity measure

In this section, we employ an alternative measure to capture geographic proximity to terrorism. Instead of relying on the inverse of the logarithmic distance between each attack and an individual's MSOA of residence, we divide the distance into ten equal-frequency groups, or deciles (with individuals in decile 10 being the closest to the attack). The results from using this measure are shown in Table B.8. While, as expected, the estimates differ in magnitude from those using the inverse logarithmic distance, the key finding remains unchanged: the effect of *Exposure* is negative and highly statistically significant. This guards against the concern that our results are solely dependent on the non-linear scaling of geographic proximity.

Table B.8: Terrorism exposure and life satisfaction:
Alternative geographic proximity measure.

	Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (decile)	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lagged value				0.001	0.001	-0.005
				(0.009)	(0.009)	(0.009)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.739	0.740	0.742	0.739	0.740	0.742
No. of individuals	21,028	21,028	21,028	21,028	21,028	21,028
No. of observations	67,941	67,941	67,941	67,941	67,941	67,941

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.9 Heterogeneity by individual characteristics

In this section, we examine heterogeneity in relation to four individual characteristics: gender, age, ethnicity and internet usage. To conduct this analysis, we estimate models that include an interaction between exposure and binary indicators that split individuals into the following groups: female vs male respondents; younger vs older respondents (aged 18-50 vs aged 50+); non-white vs white respondents; and, frequent vs infrequent internet users (everyday vs non-everyday usage). As can be seen in Table B.9, the estimate of the interaction term is far from statistically significant in all specifications, suggesting that the post-attack decline in life satisfaction is not restricted to specific population groups defined by these characteristics.

Table B.9: Terrorism exposure and life satisfaction:
Heterogeneity by individual characteristics.

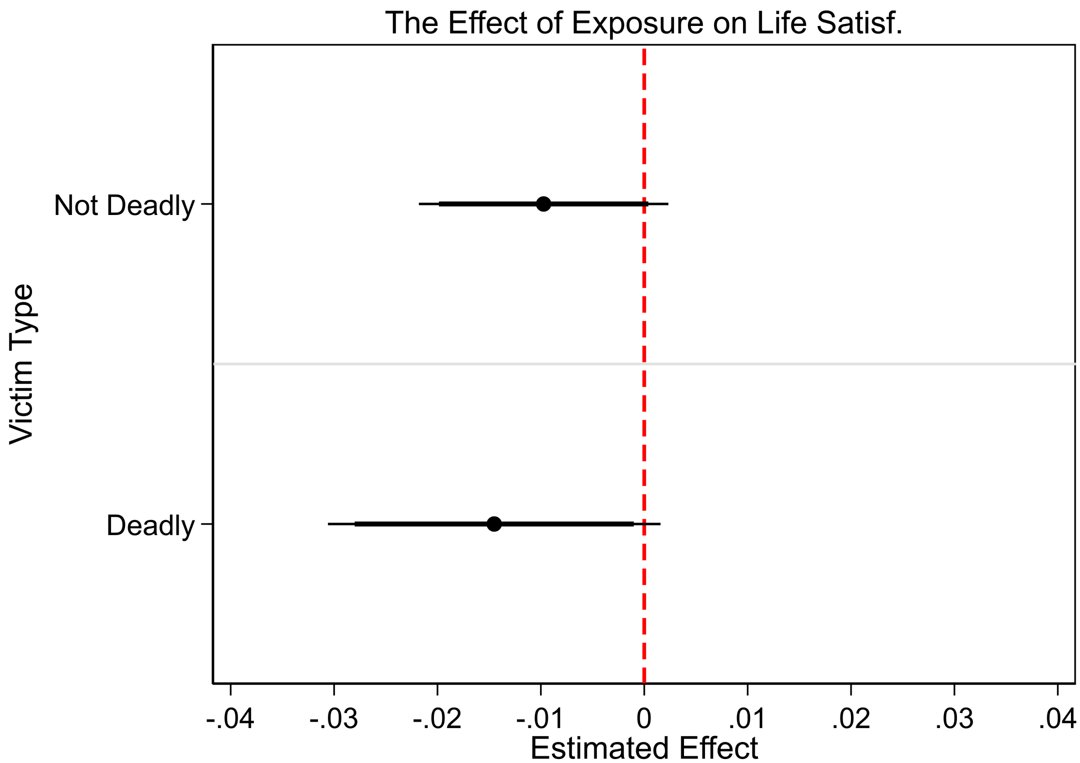
	Life satisfaction							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure	-0.016*	-0.016**	-0.015**	-0.013**	-0.016*	-0.017**	-0.015**	-0.013**
	(0.008)	(0.008)	(0.007)	(0.006)	(0.008)	(0.008)	(0.007)	(0.006)
Lagged value					-0.005	-0.005	-0.005	-0.006
					(0.009)	(0.009)	(0.009)	(0.009)
Exposure × Female	0.008				0.008			
	(0.011)				(0.011)			
Exposure × Young		0.010				0.010		
		(0.011)				(0.011)		
Exposure × Non-white			0.010				0.010	
			(0.011)				(0.011)	
Exposure × Freq. internet use				0.006				0.005
				(0.013)				(0.013)
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.742	0.742	0.742	0.741	0.742	0.742	0.742	0.741
No. of individuals	21,028	21,028	21,028	20,203	21,028	21,028	21,028	20,203
No. of observations	67,941	67,941	67,941	66,132	67,941	67,941	67,941	66,132

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's response to the life satisfaction question in the previous wave. Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.10 Heterogeneity by severity of attacks

In this section, we explore whether the intensity of the threat moderates the effect of exposure on life satisfaction. To do this, we estimate models that include an interaction with the type of victim, distinguishing between deadly and non-deadly attacks. Figure B.10 plots the marginal effects for the two attack groups. Both deadly and non-deadly attacks seem to adversely affect individuals' life satisfaction; however, the impact is notably more pronounced (both economically and statistically) in the case of deadly attacks. We interpret this as evidence that severe incidents, which evoke more intense emotional reactions and heightened perceptions of threat, lead to larger reductions in societal wellbeing in their aftermath.

Figure B.10: Heterogeneity by severity of attacks.



Notes: The estimates are based on the full model specification (with the three sets of fixed effects, controls, and lagged value). Thick (thin) lines denote statistical significance at the 90% (95%) level.

C Robustness Tests and Further Insights: Mental Distress

C.1 Using a common sample

Our analysis utilises two different samples: one for *Life satisfaction*, covering the years 1998-2020, and one for *Mental distress*, spanning 1992-2020. To ensure comparability of our findings across the two wellbeing measures, we examine the sensitivity of the *Mental distress* results (as presented in Table 8) to using the same sample as in the case of *Life satisfaction*. The estimates are little affected by this exercise, both economically and statistically, leaving our main conclusions unchanged (see Table C.1 below).

Table C.1: Terrorism exposure and mental distress: Using a common sample.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.041	-0.024	-0.015	-0.041	-0.024	-0.015
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.027***	0.027***	0.027***
				(0.010)	(0.010)	(0.010)
Exposure × Initial value [> 8]	0.085**			0.085**		
	(0.038)			(0.039)		
Exposure × Initial value [> 10]		0.084**			0.083**	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.105**			0.103**
			(0.051)			(0.051)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.769	0.769	0.769	0.770	0.770	0.770
No. of individuals	20,812	20,812	20,812	20,812	20,812	20,812
No. of observations	67,221	67,221	67,221	67,221	67,221	67,221

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

C.2 Alternative mental distress measure

In our main analysis, we adopt the Likert scoring method for measuring mental distress, which follows a 0-1-2-3 pattern. An alternative scoring method is the Caseness bimodal scoring, which assigns a value of 0 to the two lowest categories and 1 to the two highest categories, following a 0-0-1-1 pattern. The resulting total score ranges from 0 to 12, where 0 indicates the least distressed state and 12 indicates the most distressed state. As in previous studies that employ the Likert distress measure (see, e.g., Metcalfe, Powdthavee and Dolan, 2011; Dustmann and Fasani, 2016; Gray, Pickard and Munford, 2021), we examine robustness to the using the Caseness scoring method.

To capture initial conditions, we experiment with two alternative sets of individuals: (i) those with an initial distress score above 0, corresponding to both the lowest tertile and the median of the score distribution, and (ii) those with an initial distress score above 1, corresponding to the highest tertile. The results, presented in Table C.2, support once again our key findings: exposure has a positive and highly significant impact on distress for individuals with pre-existing mental vulnerabilities, while no such effect is observed for those with stronger mental health. Additionally, there is no evidence of pre-existing trends: using the lagged Caseness distress score as the outcome variable yields smaller and statistically insignificant estimates.

Table C.2: Terrorism exposure and mental distress:
Alternative mental distress variable.

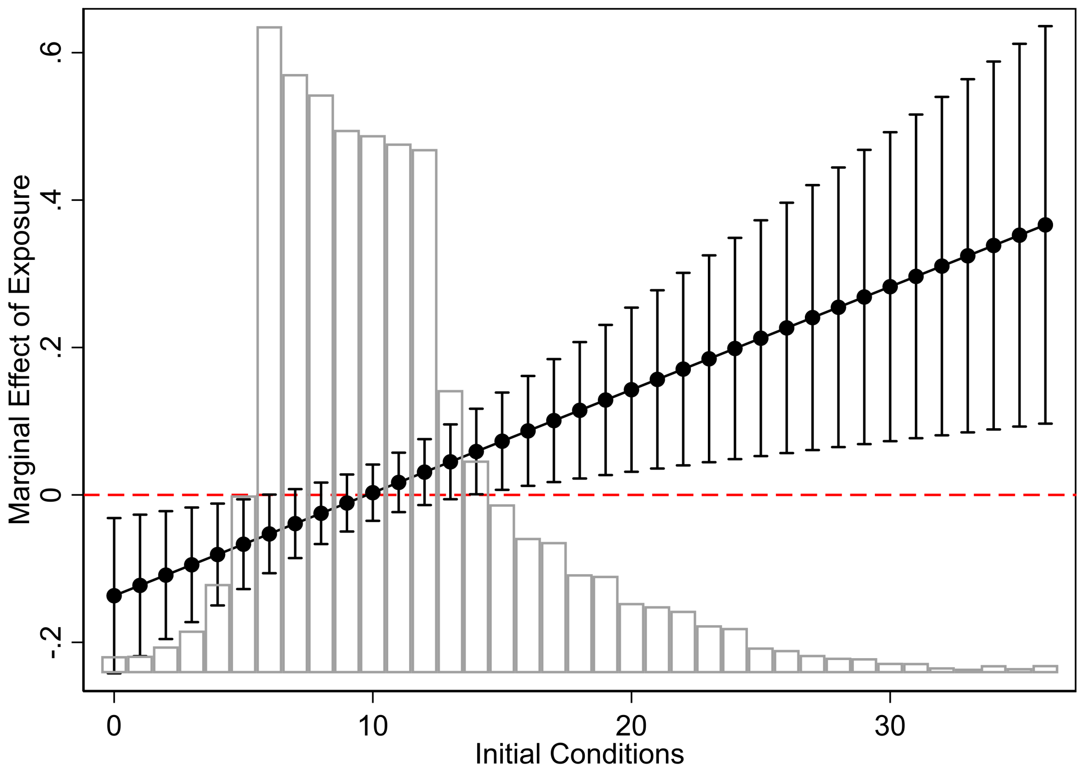
	Mental distress (0-12)				Lagged mental distress (0-12)	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.015	-0.011	-0.015	-0.011	0.001	0.006
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
Lagged value			0.056***	0.056***		
			(0.009)	(0.009)		
Exposure $\times$ Initial value $[> 0]$	0.056**		0.054**		0.025	
	(0.024)		(0.024)		(0.023)	
Exposure $\times$ Initial value $[> 1]$		0.066**		0.065**		0.018
		(0.029)		(0.029)		(0.028)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave $\times$ Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.729	0.729	0.730	0.730	0.716	0.716
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,260	80,260	80,260	80,260	80,261	80,261

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* $[> X]$ captures individuals with initial value of mental distress above X (on the 1-12 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

C.3 Interacting with a continuous measure of initial conditions

In our main analysis, we interact exposure with binary indicators that capture respondents with relatively 'poor' mental health at their first interview. Here, we estimate models that include an interaction with a continuous measure of initial distress, and then plot the marginal effects at different values of this variable. This allows us to mitigate the risk of misspecification error affecting our inferences, but also to pinpoint more precisely when mental health deterioration becomes evident. As shown in Figure C.3, the relationship between exposure and mental distress is positive and statistically significant when initial distress takes a value above 12, corresponding to the top one-third of the variable's distribution.

Figure C.3: Interacting with a continuous measure of initial conditions



Notes: This graph shows the marginal effects of exposure on mental distress at different values of initial conditions, with higher values capturing a more distressed state. The estimates are based on the full model specification (with the three sets of fixed effects, controls, and lagged value). Vertical lines signify 95% confidence intervals. The underlying bar chart is a histogram of initial conditions, showing the relative frequency of observations within each bin.

C.4 Performing the same checks as in Section B

In this final section, we perform the same set of tests and supplementary analyses as those described in Section B for life satisfaction. The corresponding results are presented in Tables C.4.1–C.4.9 and Figures C.4.1–C.4.2. Overall, the evidence obtained does not alter our conclusions.

Table C.4.1: Terrorism exposure and mental distress: Controlling for attacked MSOAs.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.061**	-0.030	-0.017	-0.061**	-0.030	-0.018
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.067***	0.067***	0.067***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.123***			0.119***		
	(0.038)			(0.038)		
Exposure × Initial value [> 10]		0.108***			0.103**	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.126**			0.122**
			(0.052)			(0.052)
Attacked MSOA	2.376***	2.387**	2.411**	2.187**	2.199**	2.221**
	(0.920)	(0.985)	(1.090)	(0.851)	(0.908)	(1.013)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

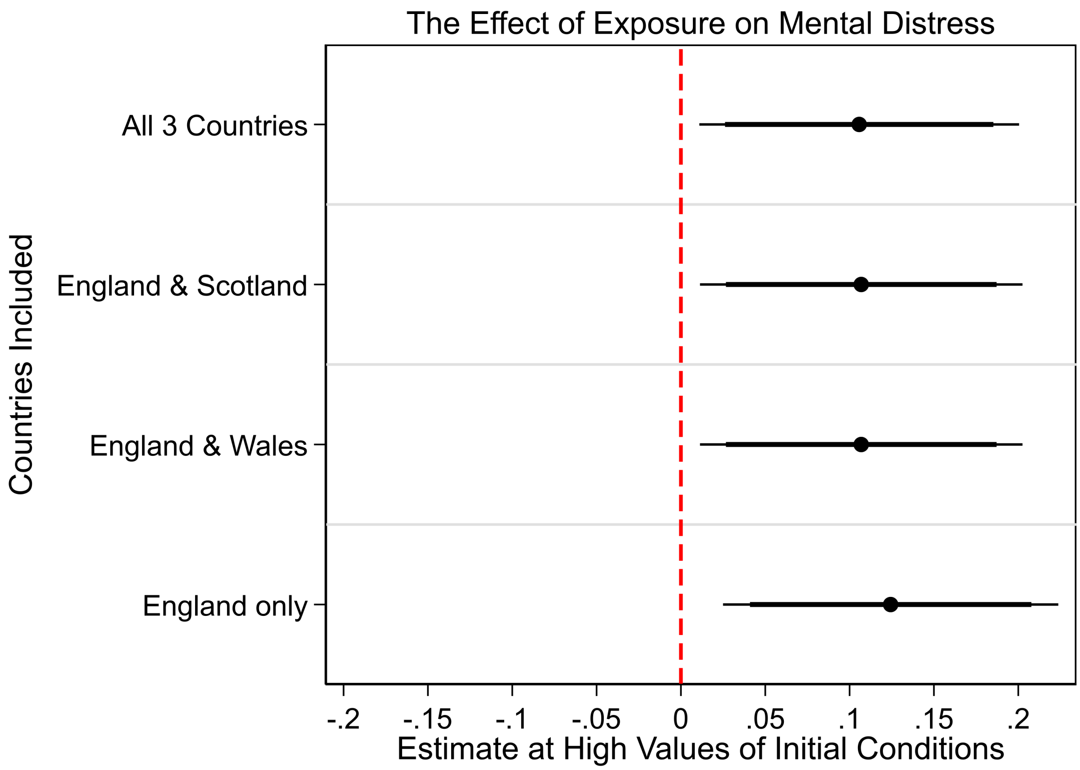
Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.2: Terrorism exposure and mental distress:
Controlling for proximity to London.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.062**	-0.032	-0.018	-0.062**	-0.032	-0.019
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.067***	0.067***	0.067***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.122***			0.119***		
	(0.038)			(0.038)		
Exposure × Initial value [> 10]		0.107***			0.102**	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.126**			0.121**
			(0.052)			(0.052)
Proximity to London	0.114	0.116	0.117	0.108	0.110	0.110
	(0.182)	(0.182)	(0.182)	(0.178)	(0.179)	(0.178)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure C.4.1: Excluding Scotland and Wales.



Notes: This figure presents the marginal effects at value 1 of the variable *Initial value* [> *12*], corresponding to individuals at the highest tertile of the initial conditions. The estimates are based on the full model specification (with the three sets of fixed effects, controls, and lagged value). Thick (thin) lines denote statistical significance at the 90% (95%) level.

Table C.4.3: Terrorism exposure and mental distress:
Keeping respondents who participated in at least five survey waves.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.056*	-0.025	-0.009	-0.057*	-0.027	-0.012
	(0.034)	(0.028)	(0.024)	(0.034)	(0.028)	(0.024)
Lagged value				0.089***	0.089***	0.089***
				(0.009)	(0.009)	(0.009)
Exposure $\times$ Initial value $[> 8]$	0.136***			0.132***		
	(0.044)			(0.045)		
Exposure $\times$ Initial value $[> 10]$		0.125***			0.122***	
		(0.046)			(0.046)	
Exposure $\times$ Initial value $[> 12]$			0.147**			0.143**
			(0.059)			(0.059)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave $\times$ Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.733	0.733	0.733	0.735	0.735	0.735
No. of individuals	18,889	18,889	18,889	18,889	18,889	18,889
No. of observations	65,689	65,689	65,689	65,689	65,689	65,689

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* $[> X]$ captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.4: Terrorism exposure and mental distress:
Closest-attack-between-waves strategy.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.091**	-0.049	-0.038	-0.092**	-0.049	-0.039
	(0.044)	(0.036)	(0.032)	(0.044)	(0.036)	(0.032)
Lagged value				0.068***	0.068***	0.068***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.148***			0.142**		
	(0.057)			(0.058)		
Exposure × Initial value [> 10]		0.115*			0.107*	
		(0.060)			(0.060)	
Exposure × Initial value [> 12]			0.152**			0.140*
			(0.077)			(0.077)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.683	0.683	0.683	0.685	0.685	0.685
No. of individuals	18,729	18,729	18,729	18,729	18,729	18,729
No. of observations	48,708	48,708	48,708	48,708	48,708	48,708

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.5: Terrorism exposure and mental distress: Using day fixed effects.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.060**	-0.034	-0.019	-0.061**	-0.035	-0.020
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.067***	0.063***	0.063***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.123***			0.120***		
	(0.038)			(0.038)		
Exposure × Initial value [> 10]		0.114***			0.108***	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.131**			0.125**
			(0.051)			(0.051)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Day FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.760	0.770	0.770	0.761	0.771	0.771
No. of individuals	24,060	24,045	24,045	24,060	24,045	24,045
No. of observations	80,263	80,210	80,210	80,263	80,210	80,210

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.6: Terrorism exposure and mental distress:
Including time distance fixed effects.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.060**	-0.029	-0.015	-0.060**	-0.030	-0.016
	(0.029)	(0.024)	(0.021)	(0.029)	(0.024)	(0.021)
Lagged value				0.068***	0.068***	0.068***
				(0.009)	(0.009)	(0.009)
Exposure × Initial value [> 8]	0.123***			0.120***		
	(0.038)			(0.038)		
Exposure × Initial value [> 10]		0.108***			0.103**	
		(0.040)			(0.040)	
Exposure × Initial value [> 12]			0.126**			0.121**
			(0.052)			(0.052)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Time Distance FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.7: Terrorism exposure and mental distress:
Alternative error clustering.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-0.059*	-0.029	-0.015	-0.060*	-0.029	-0.016
	(0.033)	(0.028)	(0.025)	(0.033)	(0.028)	(0.025)
Lagged value				0.067***	0.067***	0.067***
				(0.010)	(0.010)	(0.010)
Exposure × Initial value [> 8]	0.123***			0.120***		
	(0.045)			(0.045)		
Exposure × Initial value [> 10]		0.108**			0.103**	
		(0.048)			(0.048)	
Exposure × Initial value [> 12]			0.127**			0.122**
			(0.060)			(0.061)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of MSOAs	5,945	5,945	5,945	5,945	5,945	5,945
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [> X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.8: Terrorism exposure and mental distress:
Alternative geographic proximity measure.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (decile)	-0.011	-0.003	0.002	-0.011	-0.003	0.001
	(0.010)	(0.008)	(0.007)	(0.010)	(0.008)	(0.007)
Lagged value				0.067***	0.067***	0.067***
				(0.009)	(0.009)	(0.009)
Exposure (decile) $\times$ Initial value [>8]	0.036***			0.035***		
	(0.013)			(0.013)		
Exposure (decile) $\times$ Initial value [>10]		0.032**			0.031**	
		(0.014)			(0.014)	
Exposure (decile) $\times$ Initial value [>12]			0.038**			0.036**
			(0.018)			(0.017)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓
Wave $\times$ Week FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.762	0.762	0.762
No. of individuals	24,059	24,059	24,059	24,059	24,059	24,059
No. of observations	80,261	80,261	80,261	80,261	80,261	80,261

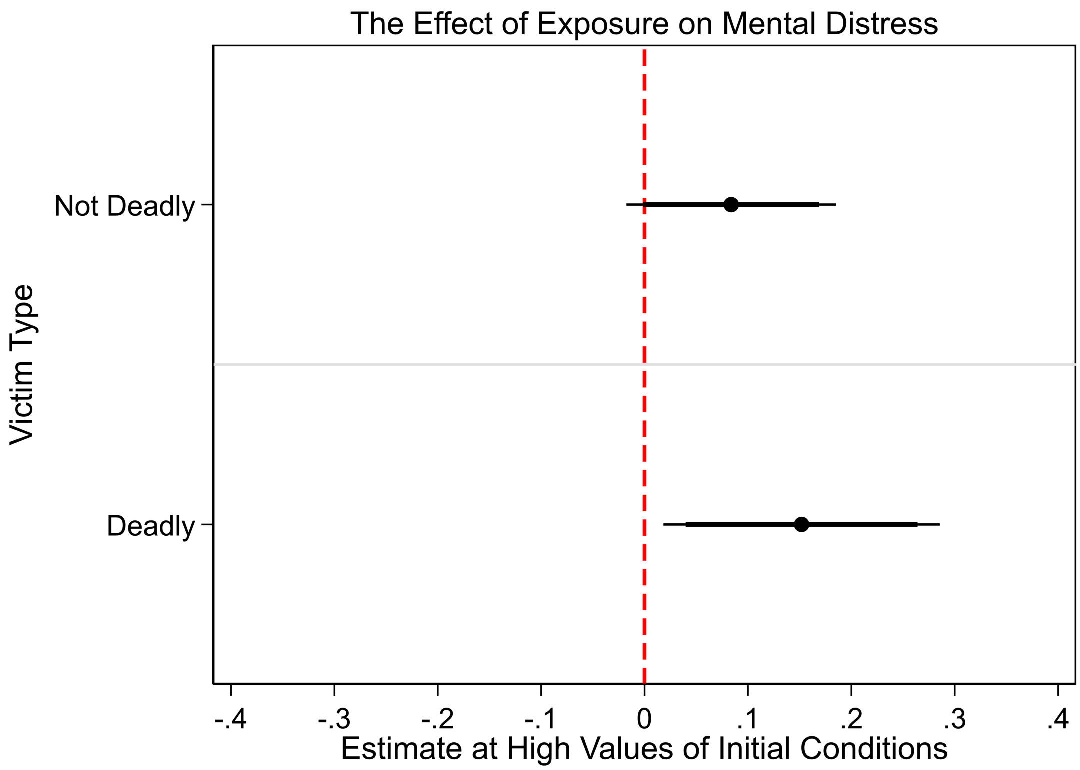
Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [$>$ X] captures individuals with initial value of mental distress above X (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4.9: Terrorism exposure and mental distress:
Heterogeneity by individual characteristics.

	Mental distress							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure	0.049*	0.050*	0.044*	0.014	0.048*	0.050*	0.040	0.012
	(0.028)	(0.026)	(0.025)	(0.024)	(0.028)	(0.026)	(0.025)	(0.024)
Lagged value					0.068***	0.068***	0.067***	0.055***
					(0.009)	(0.009)	(0.009)	(0.009)
Exposure × Female	-0.054				-0.055			
	(0.039)				(0.039)			
Exposure × Young		-0.059				-0.063		
		(0.039)				(0.039)		
Exposure × Non-white			-0.074*				-0.069*	
			(0.042)				(0.042)	
Exposure × Freq. internet use				0.001				0.001
				(0.044)				(0.044)
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓
Attack FEs	✓	✓	✓	✓	✓	✓	✓	✓
Wave × Week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.761	0.761	0.761	0.755	0.762	0.762	0.762	0.756
No. of individuals	24,059	24,059	24,059	20,499	24,059	24,059	24,059	20,499
No. of observations	80,261	80,261	80,261	69,861	80,261	80,261	80,261	69,861

Notes: The results are based on the 30-day time window to terrorism exposure. *Lagged value* is the individual's mental distress score in the previous wave. *Initial value* [$>$ X] captures individuals with initial value of mental distress above ✓ (on the 1-36 scale). Standard errors are clustered at the individual level and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure C.4.2: Heterogeneity by severity of attacks.



Notes: This figure presents the marginal effects at value 1 of the variable *Initial value* [> *12*], corresponding to individuals at the highest tertile of the initial conditions. The estimates are based on the full model specification (with the three sets of fixed effects, controls, and lagged value). Thick (thin) lines denote statistical significance at the 90% (95%) level.

D References

Bove, Vincenzo, Georgios Efthyvoulou and Harry Pickard. 2024. "Are the effects of terrorism short-lived?" *British Journal of Political Science* 54(2):536–545.

Dustmann, Christian and Francesco Fasani. 2016. "The effect of local area crime on mental health." *The Economic Journal* 126(593):978–1017.

Efthyvoulou, Georgios, Harry Pickard and Vincenzo Bove. 2024. "Terrorist violence and the fuzzy frontier: national and supranational identities in Britain." *The Journal of Law, Economics, and Organization* DOI:10.1093/jleo/ewae003.

Gray, Daniel, Harry Pickard and Luke Munford. 2021. "Election outcomes and individual subjective well-being in Great Britain." *Economica* 88(351):809–837.

Metcalfe, Robert, Nattavudh Powdthavee and Paul Dolan. 2011. "Destruction and distress: using a quasi-experiment to show the effects of the September 11 attacks on mental well-being in the United Kingdom." *The Economic Journal* 121(550):F81–F103.