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ORIGINAL ARTICLE

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Beyond the headlines: the intangible costs of terrorism

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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 Study over the same period. To get as close as possible to a causal interpretation, we exploit variation within individuals, net of potential attack-specific and aggregate temporal 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.

KEYWORDS
life satisfaction, mental health, security, terrorism, wellbeing

JEL CLASSIFICATION
I10; I31; H56; D74

1 | INTRODUCTION

The costs of terrorism are multi-dimensional, comprising both direct, tangible losses—such as those arising from casualties, property damage and emergency responses—and indirect, far-reaching impacts on social relations, economic performance and psychological resilience. These indirect effects capture the strategic intent of terrorism as a tactic: to undermine individuals' sense of security and influence public psychology (Cronin 2002, p. 33).[1] The terrorism literature has documented its deleterious effects 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; Brodeur 2018; Gaibulloev and Sandler 2019; Caldara and Iacoviello 2022). Considerably less attention, however, has been devoted to the psychological consequences of terrorism for wellbeing outcomes, despite the increasing recognition of their importance 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 its direct costs. Yet quantifying these indirect costs—particularly those concerning the wellbeing of entire populations—remains a major challenge. Declining levels of public wellbeing, reflected in rising stress levels reported in the *World Happiness Reports* since 2006 (Helliwell *et al.* 2023), underscore the growing difficulties in addressing mental health at the population level. As governments increasingly prioritize and allocate resources towards counter-terrorism efforts (Mueller and Stewart 2014), understanding the relationship between terrorism and wellbeing has become more critical than ever. The UK offers a particularly compelling case study, given the mounting evidence of deteriorating mental health—especially among its youth—and the pressure to put wellbeing at the centre of policy design (Layard and Ward 2020; Blanchflower *et al.* 2024).[2] At the same time, the UK has a long-standing history of confronting episodes of terrorism and political violence within its borders.

Against this background, our paper provides a detailed analysis of how terrorist attacks in Great Britain affect individual wellbeing, adding to the growing literature on the psychological impact of terrorism. Previous studies have found that terrorism triggers a 'complex state of negative arousal', characterized by a blend of emotions such as anxiety, fear, anger, outrage and sadness (Fisk *et al.* 2019; Godefroidt 2023; Bove *et al.* 2024). These emotional responses can help to explain shifts 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 2025). However, while much attention has focused on specific emotional reactions, the broader psychological consequences—including both cognitive-evaluative wellbeing and psychological distress—have received comparatively less scrutiny.

A small body of research documents notable declines in subjective wellbeing following terrorist incidents in the UK (Metcalfe *et al.* 2011; Hole and Ratcliffe 2020) and in other contexts (Romanov *et al.* 2012; Kim and Albert Kim 2018; Clark *et al.* 2020; Akay *et al.* 2020; Sønderskov *et al.* 2021). While they are insightful, these studies have predominantly focused on single, high-profile attacks involving numerous casualties, or relied on aggregate measures of terrorism, thereby offering only a partial understanding of its full impact on wellbeing. In reality, most terrorist attacks are small-scale, localized incidents with few victims and often no fatalities. Rather than large, emblematic events, attacks across the West are frequently carried out by lone individuals with limited resources, minimal training and little planning.

Our study contributes to this literature in four main ways.

First, we exploit individual-level data on subjective wellbeing across the general population of Great Britain over an extended period, encompassing nearly 100 attacks. This enables us to offer novel insights into the impact of a typical (average) terrorist attack on societal wellbeing. It also strengthens external validity, which could be limited if attention is restricted to prominent attacks with a large number of victims.

Second, unlike previous studies that rely on single indicators of wellbeing, we employ and compare two distinct, comprehensive measures. Specifically, we consider a single-item measure of life satisfaction and a multiple-item measure of psychological distress (Powdthavee *et al.* 2019; Gray *et al.* 2021). The former captures the cognitive-evaluative dimension of wellbeing—that is, individuals' reflective assessments of their overall life circumstances—whereas the latter, measured using the General Health Questionnaire, reflects the frequency and intensity of negative emotions and symptoms associated with psychological distress. By analysing these distinct dimensions, our paper provides a deeper understanding of the mechanisms through which terrorist attacks affect societal wellbeing.

Third, our research design makes it possible to leverage variation in 'treatment' across four key dimensions: geography, time, attack characteristics and individual traits. This enables us to explore how the intensity of terrorism exposure—in terms of both temporal proximity to a terrorist incident and the severity of attacks—affects wellbeing. In addition, it allows us to identify heterogeneous effects, shedding light on subgroups within the population, such as individuals with pre-existing mental health conditions, who may experience more pronounced impacts.

Fourth, we use our estimates to calculate the monetary equivalent for terrorism-induced wellbeing losses—what the literature interprets as the implicit willingness-to-pay (WTP) to reduce exposure to terrorism. Policymakers tasked with counter-terrorism face difficult decisions in allocating limited resources to maximize public safety and security. In this context, estimating WTP provides a clear indication of the societal value attached to reducing risk. Unlike contingent valuation studies and conjoint experiments, which rely on hypothetical scenarios and complex trade-offs, deriving WTP from subjective wellbeing data offers a more comprehensive perspective,[3] particularly for assessing the broader psychological and societal costs of terrorism.

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 Study—and produce a single dataset at the individual–wave–attack level. Following 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 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-wave attacks, net of potential time-specific confounders. 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 attacks that respondents have experienced in the last month before their interview. Although modest in absolute terms, this represents a meaningful population-level effect: individuals residing within 100 km of a 'recent' attack (i.e. one occurring within 30 days prior to the interview) exhibit a decline of approximately 0.02 units in predicted life satisfaction relative to those living beyond this distance. Turning to mental health, our analysis indicates a strong dependence on initial conditions: individuals with pre-existing mental health vulnerabilities exhibit higher distress levels following a recent terrorism shock, whereas those with relatively stronger mental states remain unaffected. This suggests that poorer baseline mental health is associated with a reduced capacity to cope with the additional stressors imposed by traumatic events such as terrorist attacks. When distinguishing between the three components of mental distress, we find that these effects can mostly be attributed to changes in social dysfunction and confidence loss. Estimating the monetary equivalent of terrorism-induced wellbeing losses reveals that an individual is willing to pay about £81 to avoid being within 100 km 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 WTP to reduce 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 Survey (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)[4] 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) in which they reside.[5] 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, for example, 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 corresponds 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 over the past few weeks they: had lost sleep over worry; felt constantly under strain; felt that they could not overcome difficulties; had been feeling unhappy and depressed; had been losing confidence; had been feeling like a worthless person; were playing a useful part in things; felt capable of making decisions; had been able to enjoy day-to-day activities; had been able to concentrate; had been able to face up to problems; had been feeling reasonably happy. Responses to each item are coded on a scale from 0 to 3, with positively framed items reverse-coded so that higher values consistently indicate greater distress. The 12 items are then added together to produce a single measure of mental distress, ranging from 0 (lowest distress) to 36 (highest distress).

Data on terrorist attacks are obtained from the Global Terrorism Database (GTD), the most comprehensive database on terrorist events worldwide from 1970 to 2020. We consider the universe of casualty-causing attacks[6] that occurred in Great Britain during the BHPS–UKHLS data collection period, comprising 97 incidents between 1992 and 2020. These attacks vary in severity, with 28 incidents resulting in at least one fatality, and 89 incidents causing at least one injury. Taken together, they span a broad range of terrorist activity across space and over time, including 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. Online Appendix Subsection A.1 provides background material on the attacks considered in our analysis.

Following Efthyvoulou *et al.* (2025), we combine the longitudinal survey data with terrorism data to create a single dataset at the individual–wave–attack level. Specifically, we assign each attack to the closest post-attack wave for individual i: attack a is linked 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.[7] Consequently, for each individual–wave observation in BHPS–UKHLS, the dataset includes one row for every attack occurring within this interval, and no rows when no attacks took place between the two dates.[8] 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 and account for the possibility that the news may take several hours to spread, we exclude observations where the attack occurred on the 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 in which 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.[9] This contains information on 53,510 individuals, 18 survey waves, and 67 attacks over the period 1998–2020 (1,032,700 observations in total). Sample 2 includes the corresponding data on *Mental distress*, and contains information on 56,746 individuals, 24 survey waves, and 97 attacks over the period 1992–2020 (1,298,893 observations in total).[10] Descriptive statistics of our key variables are provided in Table 1.[11] As can be seen in this table, the average life satisfaction is 5.2, with standard deviation 1.4 (on the 1–7 scale), whereas the average mental distress is 11.2, with standard deviation 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 Online Appendix Figure A.3).[12]

To proxy exposure to terrorism, we geolocate the attacks and calculate the distance in kilometres (km) between the centroid point of an individual's MSOA of residence and 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—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, for example, 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—that is, people believe that 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 that the event receives from local media (Böhmelt *et al.* 2020).

Online Appendix Figures A.1.1 and A.1.2 present the geographic and temporal distributions of the attacks considered in our analysis. Not surprisingly, Greater London is the part of the country with the highest exposure to terrorism (59% of all incidents, 1992–2020). However, several attacks also occurred outside London, spread across the mainland, with the distance between each MSOA and each attack having average value about 230 km and standard deviation about 155 km.[13]

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.* (2025), who extend this framework to individual, survey-based data.

Specifically, our model specification takes the form

$$Wellbeing_{iwa} = \beta_1 \ Exposure_{iwa} + \beta_2 \ \mathbf{X}_{iwa} + \theta_i + \lambda_{ad} + \phi_{wt} + \varepsilon_{iwa}, \tag{1}$$

where $Wellbeing_{iwa}$ denotes self-reported wellbeing (*Life satisfaction* or *Mental distress*) for individual i, as recorded in wave w, after attack a was perpetrated; $Exposure_{iwa}$ captures geographic

TABLE 1 Summary statistics of key variables.

	Sample 1					Sample 2				
	Mean	S.D.	Min.	Max.	Observations	Mean	S.D.	Min.	Max.	Observations
Life satisfaction	5.18	1.42	1.00	7.00	1,032,700					
Mental distress						11.19	5.44	0.00	36.00	1,298,893
Social dysfunction						6.51	2.30	0.00	18.00	1,298,893
Anxiety and depression						3.54	2.56	0.00	12.00	1,298,893
Confidence loss						1.14	1.35	0.00	6.00	1,298,893
Exposure	−0.04	0.97	−1.91	7.34	1,032,700	−0.03	0.97	−1.91	7.34	1,298,893
Geographic distance (km)	229.22	155.64	0.10	1091.10	1,032,700	226.78	154.21	0.10	1091.10	1,298,893

Notes: *Geographic distance (km)* is the distance in kilometres between an individual's MSOA and the MSOA where a casualty-causing attack occurred. *Exposure* is defined as the negative value of the log of *Geographic distance (km)*, standardized based on the full population.

proximity of individual i, interviewed in wave w, to each attack a (negative value of the log of distance in kilometres, standardized); $\mathbf{X}_{iwa}$ is a vector of individual-level control variables; θ_i, λ_{ad} and ϕ_{wt} represent individual, attack-by-temporal-distance, and wave-by-month fixed effects, respectively; and ε_{iwa} is an error term clustered at the individual level.

The inclusion of θ_i, λ_{ad} and ϕ_{wt} absorbs all time-invariant individual characteristics, and accounts for both attack-specific and broader temporal heterogeneity. Specifically, λ_{ad} captures unobserved factors related to the time (week) gap between an attack and the interview date (d)—such as evolving media coverage, shifting social and political narratives, and other intervening contextual events—while ϕ_{wt} absorbs residual temporal variation associated with the calendar month of the interview (t) within each wave. As a result, the estimate of *Exposure* (β_1) is identified from cases where the same individual experiences different geographic proximities to between-wave attacks, while average dynamics around attacks and common shocks in a given calendar month are held constant. To provide evidence that terrorism exposure results in lower levels of wellbeing, 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, for example, Epifanio *et al.* 2023; Bove *et al.* 2024).

Given that the 'typical, average attack' in our analysis involves a small number of victims,[14] we expect the effects on wellbeing to be found only—or to be most 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 individual i's interview in wave w, and those occurring outside this time window. The intuition is that geographic proximity should matter only in the short period after a terrorist event, thus the effects should be evident only 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, then a number of endogeneity issues may arise. First, it is possible that localities (MSOAs) with greater exposure to terrorism, and consequently the characteristics of their residents, may differ systematically from those with lower exposure.[15] Including individual fixed effects in equation (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 equation (1) accounts for the most important individual-specific time-varying factors that can influence wellbeing over time—including age, income, education, job status, marital status, and the presence of children in the household (see Online Appendix Table A.4 for the full list of control variables). Accounting for these characteristics helps to ensure that the estimated effect of terrorism on wellbeing is not driven by concurrent life events or changes in personal circumstances (e.g. a change in individual income that happens to coincide with higher exposure to terrorism). 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 attacks is linked to time-variant regional characteristics that also shape wellbeing.[16] 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 EFFECTS OF TERRORISM ON LIFE SATISFACTION

3.1 | Key findings

Table 2 presents the results of estimating equation (1) for *Life satisfaction*. We start from a specification that includes our exposure measure, together with individual and attack-by-temporal-distance fixed effects (column (1)), then add wave-by-month fixed effects and the control variables in a progressive manner (columns (2) and (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 (4)–(6)).[17] We find that exposure (geographic proximity to attacks) has a negative and statistically significant effect on life satisfaction, providing some first evidence of a terrorism-induced wellbeing loss for exposed individuals. Moreover, the estimates and standard errors remain unchanged across all six specifications, indicating robustness to residual temporal heterogeneity, changes in individual characteristics, and individual-specific persistence.

How large is this wellbeing loss? Comparing individuals who live within 100 km of a terrorist attack to those residing beyond this distance,[18] our estimates suggest that the former group experiences a decrease of 0.006 units in predicted life satisfaction (based on the full-year exposure period).[19] To contextualize the magnitude of this effect, we benchmark our results against the impacts of major individual life events. According to our estimates, the 0.006 unit decline corresponds to roughly 2% of the immediate effect of losing one's job, and 2% of becoming newly widowed.[20] This seemingly modest effect is nonetheless meaningful, as it captures the average impact among all individuals living within 100 km of terrorist attacks—the overwhelming majority of whom do not experience direct victimization—whereas the effects of major life events apply only to those directly affected. When aggregated across large populations, such modest individual effects may translate into non-trivial aggregate welfare losses.

As noted in Subsection 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 distinction 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).[21] The results confirm the important role of time in conditioning wellbeing responses: exposure to terrorism one month before the interview exerts

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 × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.604	0.605	0.608	0.604	0.605	0.608
No. of individuals	53,510	53,510	53,510	53,510	53,510	53,510
No. of observations	1,032,700	1,032,700	1,032,700	1,032,700	1,032,700	1,032,700

Notes: *Lagged value* is the individual's response to the life satisfaction question in the previous wave. *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from Stata package reghdfe, after absorbing fixed effects (FEs). Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

TABLE 3 Terrorism exposure and life satisfaction: the role of time.

	Life satisfaction					
	Attacks > 30 days			Attacks ≤ 30 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	−0.003	−0.003	−0.002	−0.013**	−0.012**	−0.011**
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.609	0.610	0.613	0.741	0.742	0.744
No. of individuals	53,101	53,101	53,101	21,026	21,026	21,026
No. of observations	950,456	950,456	950,456	67,932	67,932	67,932

Notes: *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

a large and statistically significant negative effect on life satisfaction, whereas exposure 2–12 months earlier yields a coefficient of magnitude comparable to the overall effect in Table 2, but not statistically significant.

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—as in the case of crime (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 recently affected by attacks—will experience lower levels of life satisfaction in a

TABLE 4 Predicted values.

Distance range	Life satisfaction
0–100 km	5.171
100–200 km	5.187
200–300 km	5.193
300–400 km	5.196
400–500 km	5.199
> 500 km	5.202

Notes: Estimates from column (6) of Table 3

given period than those farther away, which can have important repercussions for their behaviour, productivity and relationships.

Substantively, the estimated effects of recent attacks (columns (4)–(6) of Table 3) are nearly four times as large as those reported in Table 2. Specifically, individuals residing within 100 km of a recent terrorist attack (i.e. one occurring within 30 days prior to the interview) exhibit a decline of approximately 0.022 units in predicted life satisfaction relative to those living beyond this distance—with this decline corresponding to about 2% of the variable's standard deviation.[22] To facilitate further interpretation of the estimates, Table 4 presents the average predicted life satisfaction across different distance ranges from the average attack.

We next examine whether the decline in life satisfaction following recent attacks is concentrated among specific groups of individuals. For example, those who already perceive their lives as falling short may be more adversely affected by exposure to a terrorist event. In Table 5, we test whether initial conditions in life satisfaction matter for the empirical relationship that 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.[23] 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 Online Appendix Subsection B.9).

3.2 | Identification tests

As mentioned in Subsection 2.3, if self-reported wellbeing is influenced by unobserved time-varying factors, then 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) and (6)), we find that unobserved factors would need to exert at least 12 times the influence of observed factors (such as changes in age, education, income and employment status) to explain away the entire 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 equation (1) with its 'lagged value'. A statistically significant estimate in these regressions would indicate the presence of pre-existing trends—that is, omitted

TABLE 5 Terrorism exposure and life satisfaction: initial conditions.

	Life satisfaction		
	(1)	(2)	(3)
Exposure	−0.001	−0.010	−0.008
	(0.016)	(0.007)	(0.006)
Exposure × Initial value [≤ 6]	−0.011		
	(0.017)		
Exposure × Initial value [≤ 5]		−0.002	
		(0.011)	
Exposure × Initial value [≤ 4]			−0.013
			(0.014)
Individual FEs	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓
Wave × Month FEs	✓	✓	✓
Controls	✓	✓	✓
R-squared	0.744	0.744	0.744
No. of individuals	21,026	21,026	21,026
No. of observations	67,932	67,932	67,932

Notes: The results are based on the 30-day time window to terrorism exposure. *Initial value* [≤ *X*] captures individuals with initial value of life satisfaction equal to *X* or less (on the 1–7 scale). *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

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.* 2025). 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 6 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 turns 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 Online Appendix Section B.

We start by conducting additional tests to alleviate concerns about omitted heterogeneity related to the attack locations. In Online Appendix Subsection B.1, we augment equation (1)

TABLE 6 Terrorism exposure and life satisfaction: falsification tests.

	Lagged life satisfaction			Financial wellbeing		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	−0.005	−0.005	−0.004	−0.002	−0.003	−0.003
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.730	0.731	0.733	0.808	0.809	0.815
No. of individuals	21,026	21,026	21,026	20,999	20,999	20,999
No. of observations	67,932	67,932	67,932	67,835	67,835	67,835

Notes: The results are based on the 30-day time window to terrorism exposure. *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

with a variable capturing the MSOAs that were directly hit by recent attacks, whereas in Subsection 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 being closer to 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 Subsection B.3).[24]

In Online Appendix Subsection 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.[25]

In Online Appendix Subsection B.5, we check sensitivity to employing a 'closest-attack-between-waves strategy' (Efthyvoulou *et al.* 2025). 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 Online Appendix Subsections B.6, B.7 and B.8, we experiment with three variations of the baseline model. First, we account for short-term shocks on specific dates by including day fixed effects. Second, we test robustness to alternative clustering of standard errors. Third, we rely on a different measure of terrorism exposure based on deciles of geographic distance. In all cases, the core relationship holds, and our inferences do not change.

In Online Appendix Subsection 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 Online Appendix Subsection B.10, we examine whether 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—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.[26]

3.4 | Assessing the indirect costs of terrorism

Security 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 subsection, we use the 'life satisfaction approach' to assess the marginal wellbeing costs associated with exposure to terrorism in Great Britain. This approach correlates the degree of public goods (or 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 WTP to reduce exposure to terrorism—that is, how much income a person would sacrifice to hold their wellbeing constant—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, find 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 km of an attack that occurred in the last 30 days. The estimates, reported in Online Appendix Table A.5.3, suggest that being within this geographic area reduces life satisfaction by 0.01967 units on the 1–7 scale. We then take an established coefficient for income from the literature: one log point of 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 1.452 in the 30-day exposure period). The 2021 median gross annual income for all employees (full- and part-time) in the UK was £25,971 (Office for National Statistics 2023), which is equivalent to £2134.60 for the 30-day period in which the terrorism effect is active. A 1% change in income (about £21) therefore raises life satisfaction by approximately 0.00508 points. This implies that an individual is willing to pay £$(21 \times 0.01967)/(0.00508) \approx$ £81.3 to avoid being within 100 km of an attack that occurred in the last 30 days. Multiplying this figure (i.e. individual WTP) by city adult population allows us to calculate the city-specific aggregate WTP. Table 7 displays the corresponding figures for the 20 largest cities (by population) in Great Britain.

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 that 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 km of a city's centroid *per year* over our sample period. This produces the yearly city-specific adjusted WTP values reported in Table 7. As can be seen in this table, the monetary equivalent for terrorism-induced wellbeing losses ranges from £708,000 in Plymouth to £398 million in Inner London annually. This indicates that the indirect costs of terrorism may far exceed the direct (economic) costs.[27]

TABLE 7 Monetary equivalent of wellbeing loss (WTP £81.29).

Area code	Area name	Adult population (thousands)	Average no. of attacks per year	Adjusted WTP (£)	Aggregate WTP (£) (thousands)	Adjusted aggregate WTP (£) (thousands)
J01000007	Birmingham	896.9	0.16	13.01	72,906	11,665
J01000013	Bradford	266.5	0.48	39.02	21,662	10,398
J01000015	Bristol	472.4	0.16	13.01	38,400	6144
J01000020	Cardiff	290.6	0.16	13.01	23,619	3779
S12000036	City of Edinburgh	439.2	0.12	9.75	35,704	4284
J01000028	Coventry	314.2	0.16	13.01	25,538	4086
J01000031	Derby	209.3	0.44	35.77	17,016	7487
S12000049	Glasgow City	525.9	0.12	9.75	42,750	5130
E13000001	Inner London	2845.4	1.72	139.81	231,294	397,826
J01000050	Kingston upon Hull	230.7	0.20	16.26	18,749	3750
J01000051	Leeds	415.1	0.44	35.77	33,745	14,848
J01000052	Leicester	328.3	0.16	13.01	26,684	4269
J01000054	Liverpool	484.6	0.44	35.77	39,393	17,333
J01000058	Manchester	453.1	0.48	39.02	36,830	17,678
J01000062	Newcastle upon Tyne	241.3	0.04	3.25	19,612	784
J01000067	Nottingham	261.5	0.36	29.26	21,253	7651
J01000072	Plymouth	217.9	0.04	3.25	17,710	708
J01000082	Sheffield	456.0	0.52	42.27	37,067	19,275
J01000087	Southampton	220.5	0.20	16.26	17,922	3584
J01000095	Stoke-on-Trent	222.4	0.56	45.52	18,076	10,123

Notes: Population figures are for the resident population aged 16 and over in 2020, obtained from Nomis (England and Wales) and the National Record of Scotland. Area codes beginning with J0 correspond to major towns and cities; those beginning with S12 correspond to Scottish council areas; and those beginning with E13 denote inner or outer London. Calculations are based on the full precision of the estimated coefficients.

4 | THE EFFECTS OF TERRORISM ON MENTAL DISTRESS

4.1 | Key findings and identification tests

We now explore the effects of terrorism on psychological distress, capturing the frequency and intensity of negative emotions and symptoms associated with mental health difficulties. Panel A of Table 8 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—for example, 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 8, the exposure estimates for attacks that took place in the last month are three 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 may reflect the fact that only a subset of the population experiences heightened mental distress in response to terrorism. A key factor associated with mental health deterioration following traumatic events is the presence of pre-existing vulnerabilities. Individuals with prior mental health disorders are more likely to

TABLE 8 Terrorism exposure and mental distress: main results.

	Mental distress					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
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				0.082***	0.083***	0.073***
				(0.004)	(0.004)	(0.004)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.606	0.607	0.612	0.609	0.609	0.614
No. of individuals	56,746	56,746	56,746	56,746	56,746	56,746
No. of observations	1,298,893	1,298,893	1,298,893	1,298,893	1,298,893	1,298,893

	Attacks > 30 days			Attacks ≤ 30 days		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
Exposure	0.007	0.007	0.007	0.023	0.021	0.018
	(0.005)	(0.005)	(0.005)	(0.021)	(0.021)	(0.021)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.608	0.608	0.614	0.758	0.758	0.762
No. of individuals	56,349	56,349	56,349	24,057	24,057	24,057
No. of observations	1,203,699	1,203,699	1,203,699	80,249	80,249	80,249

Notes: *Lagged value* is the individual's mental distress score in the previous wave. *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

experience worsening symptoms after a traumatic event, as ongoing stress can impair emotional regulation and coping capacity (Bryant 2019). To test this argument, we interact exposure with an indicator capturing respondents who displayed relatively poor mental health at their first interview. Specifically—and consistent with psychological research that treats GHQ scores above 11 or 12 as indicative of 'mental illness' (see, for example, Goldberg *et al.* 1997)—we define the mentally distressed group as those with an initial distress score above 12, corresponding to the upper third of the score distribution.

The results suggest that individuals with pre-existing conditions are indeed more susceptible to experiencing mental health deterioration following a terrorist attack. As can be seen in Table 9, exposure exerts a positive and statistically significant effect on distress among people with mental vulnerabilities (as inferred from the sum of the estimates of *Exposure* and the interaction term), and this effect vanishes for individuals with stronger baseline mental health (as inferred from the estimate of *Exposure* alone). When focusing on the mentally distressed group and comparing individuals residing within 100 km of a terrorist attack to those living beyond this distance,

TABLE 9 Terrorism exposure and mental distress: heterogeneity by initial conditions.

	Mental distress		
	(1)	(2)	(3)
Exposure	−0.010	−0.012	−0.017
	(0.021)	(0.021)	(0.021)
Exposure × Initial value [> 12]	0.122**	0.123**	0.131**
	(0.053)	(0.053)	(0.052)
Individual FEs	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓
Wave × Month FEs		✓	✓
Controls			✓
R-squared	0.758	0.758	0.762
No. of individuals	24,057	24,057	24,057
No. of observations	80,249	80,249	80,249

Notes: The results are based on the 30-day time window to terrorism exposure. *Initial value* [> 12] captures individuals with initial value of mental distress above 12 (on the 0–36 scale). *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

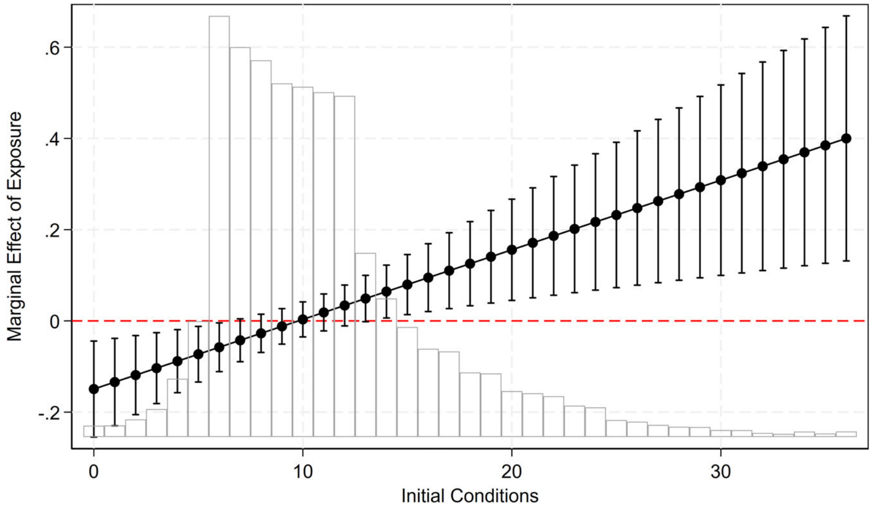

FIGURE 1 Interacting with a continuous measure of initial conditions. *Notes*: This graph shows the marginal effects of exposure on mental distress at different values of initial conditions, with higher values capturing a more distressed state. The estimates are based on the full model specification (with the three sets of fixed effects and controls). 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.

our estimates indicate that the former experience an increase of 0.21 units in predicted mental distress—which accounts for about 4% of the variable's standard deviation.

We further estimate a specification that interacts exposure with a continuous measure of initial distress, then plot the marginal effects at different values of this variable. This approach reduces the risk of misspecification bias, and allows us to identify the range of initial conditions under which mental health deterioration becomes evident. As shown in Figure 1, the relationship between exposure and mental distress is positive and statistically significant when initial

TABLE 10 Terrorism exposure and mental distress: falsification tests.

	Lagged mental distress			Physical health		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.023	0.024	0.019	0.015	0.019	0.023
	(0.021)	(0.022)	(0.022)	(0.035)	(0.035)	(0.035)
Exposure × Initial value [> 12]	0.064	0.063	0.066	−0.070	−0.073	−0.052
	(0.051)	(0.051)	(0.051)	(0.071)	(0.071)	(0.070)
Individual FEs	✓	✓	✓	✓	✓	✓
Attack × Time Dist. FEs	✓	✓	✓	✓	✓	✓
Wave × Month FEs		✓	✓		✓	✓
Controls			✓			✓
R-squared	0.750	0.751	0.753	0.878	0.878	0.880
No. of individuals	24,057	24,057	24,057	19,257	19,257	19,257
No. of observations	80,249	80,249	80,249	61,509	61,509	61,509

Notes: The results are based on the 30-day time window to terrorism exposure. *Initial value* [> 12] captures individuals with initial value of mental distress above 12 (on the 0–36 scale). *Time Dist.* is the distance, in weeks, between the attack and the interview date. R-squared values are within (unadjusted) from reghdfe, after absorbing fixed effects. Standard errors are clustered at the individual level and reported in parentheses.
*, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

distress exceeds value 12, in line with our threshold-based classification of mentally distressed individuals.

To strengthen the credibility of our results, we perform the two falsification tests of Subsection 3.2. First, we replicate the regressions of Table 9 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.[28] Although ongoing mental health issues and chronic stress can eventually lead to 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 10, both exercises return estimates that are smaller and statistically less robust than those reported in Table 9, 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 the Graetz (1991) 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* and *Confidence loss*.[29] If anything, one would expect terrorism to influence 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.

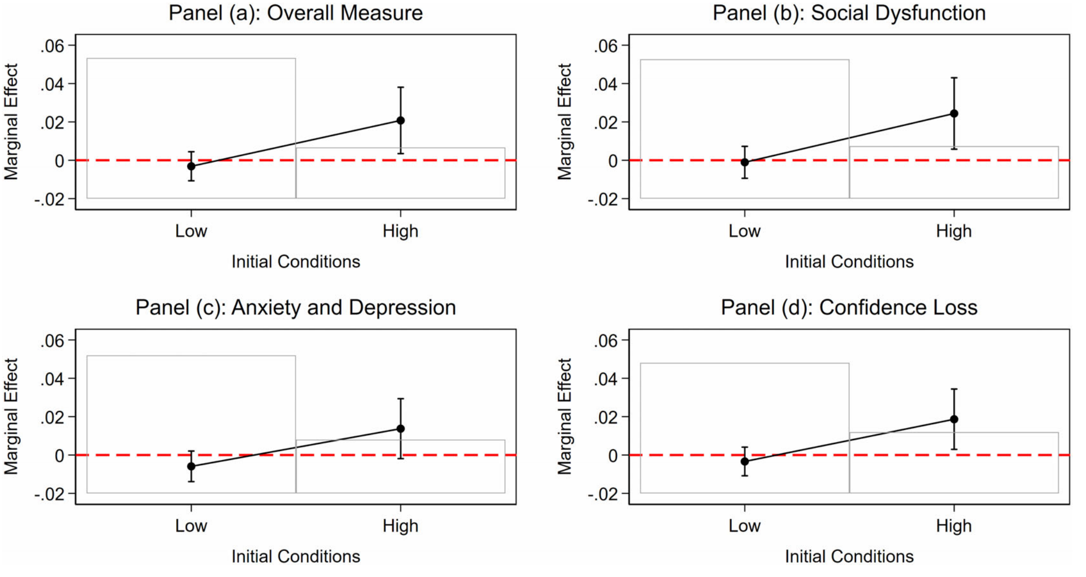

FIGURE 2 Terrorism exposure and mental distress: decomposing the effects. *Notes*: This figure shows the marginal effects of exposure on the overall measure and the three sub-measures of *Mental distress* at values 0 and 1 of initial conditions. All measures have been standardized. 'Low' (value 0) refers 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.

Figure 2 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.[30] 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 factor *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 9) through a large number of auxiliary analyses, detailed in Online Appendix Section C. First, we restrict the sample to include the same individual–wave–attack observations as in the case of *Life satisfaction*, which allows us to address concerns about the comparability of the results across the two wellbeing measures (see Subsection 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 Subsection C.2). Third, we perform the same set of tests and supplementary analyses as those described in Subsection 3.3 for life satisfaction (see Subsection C.3). 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 attack-specific and aggregate temporal 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 impact the mental health of the general population, individuals with pre-existing psychological vulnerabilities display elevated levels of distress in the aftermath of recent attacks. This difference may reflect the nature of the two outcomes: life satisfaction is a general evaluative judgement that responds to external shocks for most individuals, whereas mental health problems represent more serious conditions that primarily deteriorate when underlying vulnerabilities are present. In other words, stressors appear to lower perceived quality of life broadly, but translate into clinical-type symptoms mainly among those already at risk.

This study represents a first attempt to identify the causal impact of a 'typical' 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, the analysis focuses on Great Britain, a region with a long history of terrorism within its borders. This setting offers a valuable case study and arguably a 'hard case' given the likely presence of coping mechanisms within the population that mitigate the psychological effects of terrorism. The relatively high frequency of low-intensity attacks may have led to a degree of desensitization, as exposure to recurring violence can normalize such events and foster resilience. Consequently, individuals may return more quickly to baseline wellbeing levels despite the initial psychological shock. This dynamic underscores the need to examine the impact of terrorism in contexts where attacks are far less frequent.

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 recognize 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 measures of subjective wellbeing. A valuable direction for future research would be to examine the mental health consequences of terrorism using more objective indicators that do not depend on personal assessments, such as medical records or clinical diagnoses, as proposed by Sønderskov *et al.* (2021). Integrating subjective and objective measures would allow for a more comprehensive and accurate understanding of the impact of terrorism on mental health.

Finally, it is crucial to evaluate the effectiveness of policies designed to mitigate the psychological consequences of terrorism. Examining the impact of mental health interventions, community resilience programmes, and counter-terrorism strategies on reducing the mental health burden of terrorist incidents represents a promising avenue for future research. Such assessments are essential for informing evidence-based policy-making, and improving the design and implementation of measures that strengthen psychological resilience and lessen the adverse effects of terrorism.

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ENDNOTES

[1] While some studies find that certain attacks can elicit short-term feelings of solidarity or unity ('all in it together' effects), these responses typically arise through shared experiences of fear, anxiety and collective vulnerability (Falcó-Gimeno *et al.* 2023; Efthyvoulou *et al.* 2025). In that sense, even positive social reactions remain rooted in the psychological mechanisms that terrorism seeks to activate.

[2] 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.

[3] See Dolan *et al.* (2019) for a discussion of the advantages of using subjective wellbeing measures to value intangible benefits or costs.

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

[5] MSOAs comprise between 2000 and 6000 households, and have a resident population between 5000 and 15,000 people. There are approximately 8600 MSOAs or equivalent areas in Great Britain.

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

[7] Online Appendix Subsection A.2 provides a hypothetical example illustrating the process of constructing the individual–wave–attack-level dataset.

[8] As shown in Online Appendix Table A.5.1, a specification that compares attacks within 100 km to those occurring more than 100 km away produces the same estimate as a specification that compares attacks within 100 km to both distant attacks and periods with no attacks. This indicates that distant attacks have the same estimated effect on wellbeing as no attacks at all.

[9] Focusing on wave-on-wave data ensures that terrorism exposure is temporally aligned with the period over which outcomes may adjust. It also enables us to capture short-term within-individual changes in outcomes and control variables, accounting for contemporaneous shifts in socioeconomic conditions and other confounders.

[10] 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.

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

[12] Our samples exclude the first wave in which each outcome is observed in BHPS–UKHLS, as we retain only observations for which individuals' 'mover' status is known and wave-on-wave information can be constructed. Wave 19 (the first wave of the UKHLS) is also left out because it contains only new respondents. The other excluded waves either correspond to periods without any attacks (waves 12, 13 and 18) or lack data on the outcome variable (*Life satisfaction* in wave 11).

[13] Focusing on the London attacks, the mean distance between each MSOA and the attack locations is 199 km (standard deviation 165 km) for the full sample, and 15 km (standard deviation 7 km) for respondents residing in London.

[14] 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.

[15] Terrorist attacks are more likely to occur in urban and densely populated areas. Such areas also differ from rural areas in residents' socioeconomic characteristics, including age composition, education levels, household structure, and income.

[16] 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).

[17] Individual fixed effects account for time-invariant unobserved heterogeneity, while the lagged dependent variable (LDV) captures persistence in life satisfaction over time. We acknowledge that combining fixed effects with an LDV can introduce a small-sample bias (Nickell 1981), therefore we do not rely on this specification for identification.

Instead, we show that the estimated effect of *Exposure* is similar with and without the LDV, and that exposure does not significantly predict the LDV when it is treated as the dependent variable (see Table 6). These results indicate that our findings are not sensitive to alternative ways of modelling the outcome dynamics.

[18] To put this into perspective, the 100 km distance is equivalent to the longest physical distance across Greater London (about 60 km) plus the surrounding areas. This allows us to capture the spillover effects of terrorism on people living in neighbouring regions. Prior studies also support using a 100 km threshold to capture local exposure to terrorism. For example, Falcó-Gimeno *et al.* (2023) find that the electoral impact of terrorist attacks is substantially stronger for populations located within 100 km of an incident.

[19] To obtain this value, we compare predicted life satisfaction at two specific benchmarks: the average distance of individuals living within 0–100 km of the attack, and the average distance of those residing more than 100 km away. Notably, when we instead compare the most exposed individuals (those with the minimum value of distance) to the least exposed ones (those with the maximum value of distance), the corresponding decline in predicted life satisfaction is five times as large, amounting to 0.03 units.

[20] We calculate the effects using a binary indicator that equals 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 Online Appendix Subsection A.5.

[21] 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—that is, we consider one month as a time window to terrorism exposure.

[22] When we compare the most exposed individuals to the least exposed ones, the decline in predicted life satisfaction is approximately 0.105 units, corresponding to about 7% of the variable's standard deviation.

[23] The distribution of life satisfaction is highly skewed to the left, with 50% of the observations corresponding to the top two values (6 and 7), and less than 30% of the observations corresponding to the bottom four values (1–4).

[24] We further check robustness by restricting the sample to observations from the UKHLS period (2009–2020), which, by design, interviews a larger number of individuals than the BHPS. Focusing on this more recent period—where survey coverage and the GTD documentation are most extensive—confirms that the estimated effects are not driven by earlier observations and remain qualitatively unchanged.

[25] In addition, we test whether terrorism exposure predicts sample attrition by estimating regressions in which the outcome is an indicator for attrition in wave $t+1$ (or for permanent attrition, defined as absence from all waves $t+1$ to $t+3$), and the key regressor is exposure at wave t. These regressions yield economically and statistically insignificant estimates, indicating that terrorism exposure does not predict subsequent attrition.

[26] Using other proxies to gauge the event's severity (e.g. separating attacks based on 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.

[27] For instance, the total economic costs of five terrorist attacks that took place in the UK in 2017 were about £172 million. See https://www.gov.uk/government/publications/counter-terrorism-strategy-contest-2023/annex-d-estimating-the-cost-of-terrorist-attacks (accessed 4 April 2026).

[28] The PCS 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.

[29] The *Social dysfunction* sub-index includes items related to coping with everyday activities and decision-making (e.g. 'Been able to enjoy your normal day-to-day activities?', 'Been able to concentrate on whatever you're doing?'). The *Anxiety and depression* sub-index captures emotional strain and psychological distress (e.g. 'Lost much sleep over worry?', 'Felt constantly under strain?'), while the *Confidence loss* sub-index reflects self-perception and self-worth (e.g. 'Been thinking of yourself as a worthless person?').

[30] For comparability purposes, we use the standardized values of all four indices.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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