Risk Aversion in the Shadow of Terror

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Economic literature highlights the disproportionate high economic impacts of terror attacks, relative to the immediate damage inflicted by these attacks. This puzzle warrants a better understanding of the precise mechanisms driving this phenomenon. Utilizing data from the Global Terrorism Database and rich geocoded data on risk preferences, we apply a difference-in-differences approach to compare individuals residing within a 25-kilometer radius of an attack to those living further away. Our findings indicate that terror attacks cause an immediate and notable decline in risk preferences in the treatment group. The extent of this effect varies with the sentiment and reach of news coverage on the attack. Additionally, we observe shifts in risky behaviors, including a reduced likelihood of self-employment or stock ownership. We further show that diminished happiness mediates the relationship between terror exposure and changes in risk preferences. These results imply that shifts in risk preferences may contribute to the broader economic costs of terrorism.

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1. Introduction

In the twenty-first century, terror attacks have been one of the most publicly debated acts of violence, not only due to their tragic loss of human life but also because of their far-reaching societal and economic consequences. Devastating terror attacks include the 9/11 attacks on the World Trade Center and the Pentagon in 2001, the Beslan School Siege in Russia in 2004, the Madrid train bombings in 2004, the London train bombings in 2005 and the Paris attacks in 2015. Research documents significant economic damage from terror attacks, including reductions in total earnings and GDP (Brodeur, 2018; Brodeur and Yousaf, 2022; Abadie and Gardeazabal, 2003). Strikingly, these economic losses often far exceed the direct physical destruction caused by the attacks, suggesting that psychological factors may play an important role. In this sense, Becker and Rubinstein (2011) argue that the *uncertainty* about prospective terror attacks plays an important role in understanding the consequences of terror attacks.[1] In decisions under uncertainty, *risk preferences* are crucial in understanding individuals' economic choices.

Research question. In this study, we examine the hypothesis that exposure to terror attacks increases risk aversion among individuals, which may explain the disproportionate negative economic impacts of these events. Terror attacks impacting risk preferences can have significant implications, as they shape economic decision-making, influencing behaviours ranging from occupational choice to the decision to migrate (Dohmen et al., 2011; Dustmann et al., 2020). Despite the substantial body of research on the economic effects of terror attacks (e.g. Blomberg, Hess, and Orphanides, 2004; Frey, Luechinger, and Stutzer, 2007a; Gould and Stecklov, 2009; Quintana-Domeque and Ródenas-Serrano, 2017), the potential impact of terror attacks on risk preferences is not yet explored. As most attacks are only witnessed by a few people in person, news media play a crucial role in forming public opinion and triggering personal reactions. We acknowledge this by including an extensive media sentiment analysis in our study.

Becker and Rubinstein (2011) argue that emotions are an important factor in the relationship between terror attacks and economic decisions. They argue that emotions affect beliefs and behavior, which in turn can explain the detrimental effects of terror attacks on economic outcomes. Building on that insight, we study the psychological mechanisms driving this change in risk preferences. According to the Appraisal-Tendency Framework (Lerner and Keltner, 2000, 2001; Han, Lerner, and Keltner, 2007), we hy-

[1] However, Becker and Rubinstein (2011) study the deviation of subjective from objective beliefs.

pothesize that emotions triggered by the attacks–such as a decline in happiness–may alter how individuals assess risks, leading to increased risk aversion. This hypothesis is supported by prior work showing that emotions influence risk preferences in other contexts, such as financial decision-making and responses to adverse life events (Meier, 2022; Necker and Ziegelmeyer, 2016; Guiso, Sapienza, and Zingales, 2018). We explore this channel by examining the role of emotions, which are shown to affect risk-taking behavior.

Empirical approach. Identifying the causal impact of terror attacks on risk preferences presents several challenges, particularly the risk of confounding factors, i.e., unobserved factors that are associated with the occurrence of a terror attack and risk preferences that would bias a simple OLS-estimation. These confounding factors could be, for example, population density, regional economic activity or individual level factors, just to name a few. To address this concern, we employ a staggered difference-in-differences (DiD) design and event-study analyses, comparing individuals living in regions affected by terror attacks to those in unaffected regions. Our identification strategy relies on two-way fixed effects (TWFE) regressions, including both individual- and year-fixed effects, as well as regional fixed effects. This way, we account for permanent differences at the individual and regional level, as well as time trends. We verify the plausibility of the parallel trends assumption by demonstrating common pre-trends in risk preferences between treated and control group in our event study analysis. This empirical approach allows us to consistently estimate the effect of terror attacks on individual risk preferences.[2] The event study analysis allows us to study the dynamics of the effect, *e.g.*, whether the effect on risk preferences is permanent or transitory, a subject that is of immense interest (Schildberg-Hörisch, 2018). Importantly, in our study, we make use of the geoinformation of the individuals' residences to determine the treatment assignment in a data driven approach. For this, we determine treatment radii around the individuals' residences and expand these systematically to understand how distance to the terror attacks moderates the effect sizes. This way, we also avoid relying on arbitrary administrative borders.

[2]A vast body of literature shows that heterogeneous and dynamic treatment effects pose serious challenges in staggered DiD designs (Baker, Larcker, and Wang, 2022; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Borusyak, Jaravel, and Spiess, 2024; de Chaisemartin and D'Haultfœuille, 2020). We show that our results are robust to heterogeneous treatment effects.

Data. We construct a new data set from three sources to investigate the effects of terror attacks on risk preferences and risky behaviours, such as holding financial assets, being self-employed, smoking, and physical activity. Our primary data set is the Socio-Economic Panel (SOEP) (Goebel et al., 2019), a large, nationally representative household survey that includes individual-level measures of risk preferences over a 13-year period. Using respondents' geo-information on their place of residence, data is merged from the Global Terrorism Database (GTD), which provides detailed information on terror attacks in Germany. Finally, we use data from the universe of news compiled by LexisNexis to analyze how the sentiment and reach of news coverage moderates the effect of terror attacks on risk preferences.

Results. Our findings show that terror attacks increase individuals' risk aversion by approximately 2% of a standard deviation. Moreover, the effect persists up to two years. We argue that the transitory nature of the effect could have welfare consequences. For example, if risk preferences change over time, insurances, which could have been signed in times with higher risk aversion, might become suboptimal once the level of risk aversion converges back to it's previous level. This poses a challenge to the social planner, with important implications for social welfare (*e.g.*, Harrison and Ng, 2016). The impact is highly localized, with the strongest effects observed for individuals living within 25 kilometres of an attack. It decreases in magnitude of the radius and completely vanishes at radii larger than 75 kilometres. Our analysis also reveals that the effects are largest for individuals without migration background and individuals in East Germany, the region that historically belonged to the socialist German Democratic Republic (GDR).

We further find that emotions are an important channel in the relationship between terror attacks and risk preferences. Specifically, we find that terror attacks decrease the frequency individuals feel happy and we also find that risk preferences are associated with happiness. Overall, this evidence has not been shown in the literature so far.

We also find that the sentiment and coverage of news related to the attack significantly amplify these effects. A more negative article sentiment may imply more violent language, a focus on losses and grief, or the risk of a future attack. Individuals exposed to more negative news sentiment exhibit larger and longer-lasting declines in risk preferences.

One question is whether these changes in risk preferences translate into actual risky behaviors. Among the attacks with at least one wounded or killed victim, the probability of being self-employed decreases by about 2 percentage points. The probability of engaging actively in sport increases by 2 percentage points, indicating higher investments into health, which decreases the risk of illness. Among the attacks that received high news coverage, stock market participation decreased by about 2 percentage points. These findings suggest that terror attacks change economic behaviors associated with individuals' risk preferences, *e.g.*, individuals may choose less risky occupations or opt for more secure assets.

Literature & Contribution. First, our paper contributes to the literature on violence and risk preferences. Prior studies have shown that violence increases risk aversion, such as casualties in Burundi's civil war (Voors et al., 2012), drug-related violence in Mexico (Brown et al., 2019), and violence in Afghanistan (Callen et al., 2014). Other research on post-election turmoil in Kenya reveals increased risk-taking in some cases (Jakiela and Ozier, 2019). While these studies focus on other types of violence, our contribution lies in examining the impact of terror attacks on risk preferences. Further, we provide direct evidence that emotional responses are an important channel in the relationship between terror attacks and changes in risk preferences.

Wang and Young (2020) show that an increase in terror attacks reduces equity fund flows and increases flows into government bonds, but it is unclear whether this reflects increased risk aversion or expectations of lower returns. Our study contributes by providing a direct measure of changes in risk preferences following terror attacks.

We also contribute to the literature on the economic effects of terrorism. Prior studies show that terror reduces GDP in the Basque country by 10% (Abadie and Gardeazabal, 2003), decreases employment and earnings in the U.S. (Brodeur, 2018), and negatively impacts tourism (Enders, Sandler, and Parise, 1992), well-being (Frey, Luechinger, and Stutzer, 2007b), and real estate values (Besley and Mueller, 2012). We contribute to this literature by focusing on the effect of risk preferences and risky economic behaviors, factors which can potentially explain the massive economic effects documented in the literature.[3]

While our study is the first to examine the effect of terror attacks on risk preferences, we also contribute to the broader literature on the formation of risk preferences. Previous work links risk preferences to historical stock returns (Malmendier and Nagel, 2011), pay cycles (Akesaka et al., 2021), and natural disasters (Avdeenko and Eryilmaz,

[3]Other related studies include the effects of mass shootings (Ang, 2021; Soni and Tekin, 2023; Brodeur and Yousaf, 2022).

2021b).

We also contribute to the economics of crime literature (Levitt, 1997; Becker, 1968; Draca, Machin, and Witt, 2011; Brodeur and Yousaf, 2022), including the literature on the economics of victimization (*e.g.* Bindler, Ketel, and Hjalmarsson, 2020; Bindler and Ketel, 2022; Card and Dahl, 2011) and to research on the formation of preferences more generally (*e.g.* Roth and Wohlfart, 2018; Malmendier and Nagel, 2011; Alsan et al., 2023).

Section 2 provides conceptual insights into the relationship between emotions and risk attitudes, Section 3 presents our data sources, and Section 4 introduces our staggered DiD design. We devote Section 5 to the presentation of our results and Section 6 discusses and concludes.

2. Emotions and risk preferences

Distinguishing transitory and permanent shocks. A major question in economic research is whether economic preferences are static economic primitives (Stigler and Becker, 1977), or if they follow life-cycle trends and respond to events. Figure 1 displays the life-cycle theory of risk preferences, as discussed in the overview of Schildberg-Hörisch (2018, p. 142). According to this theory, risk preferences vary systematically with age. As individuals age, they become more risk averse. However, permanent and temporary shocks cause risk preferences to deviate from this life-cycle trajectory. Permanent shocks cause a systematic shift in risk preferences, which results in a different age-trajectory until they will eventually return to the predicted level. Examples for these shocks are economic crises, natural catastrophes, or violent conflict. In contrast, temporary variation, *e.g.*, variance around this life-cycle, could be caused by changes in emotions, self-control, or stress. Both forms of shocks have important implications on how economists perform welfare analyses. For instance, if temporary variations in risk preferences occur, it might happen that any form of insurance, which was optimal when risk aversion was high, could be altered suboptimal once the level of risk aversion converges back to the individuals' "set point." Our study contributes to this literature by testing whether changes in risk preferences due to terror exposure are permanent or temporary.

Emotions. Emotions and economic decision making are deeply connected. This is especially true for risky choices (Loewenstein, 2000; Lerner et al., 2015; Meier, 2022). Emotions determine how we evaluate different states of the world and how we respond to different states. For instance, when confronted with a pleasant state of the world, we tend to evaluate it positively, which is reflected by an increase in happiness. Consequently, we perform actions to realize this pleasant state of the world. In contrast, if we are confronted with a major threat, we feel fear and display a "Fight-or-flight" response (Keltner and Gross, 1999; Bach and Dayan, 2017). As these two examples illustrate, emotions are an important component in economic decision making, especially in decisions under risk. Three major frameworks dominate the literature on the relationship between emotions and risk preferneces. These are the Appraisal-Tendency, the Feelings-as-Information and the Mood Maintenance Framework (Meier, 2022). In the following, we provide a short overview on these three frameworks.

The Appraisal-Tendency Framework postulates that emotions change an individuals' appraisal of a state of the world (Lerner and Keltner, 2000, 2001; Han, Lerner, and Keltner, 2007). For example, happiness is associated with a feeling of individual control and, thus, with optimistic appraisals. Conversely, fear is associated with a feeling of low individual control and leads to more cautious appraisals. Happiness is predicted to increase individuals' willingness to take risks (Lerner and Keltner, 2000; Ferrer et al., 2017).

Under the framework of Feelings-as-Information, individuals tend to overweight information that is consistent with their emotions. When individuals experience negative emotions, they will overweight adverse effects of risky choices, while the opposite holds for positive emotions (Schwarz and Clore, 1983; Schwarz, 2012).

Finally, the Mood Maintenance Framework conjectures that individuals who feel positive emotions strive to maintain those. Subsequently, these individuals will avoid taking risks in order to maintain the current mood (Isen and Patrick, 1983).

Among these frameworks, the Appraisal-Tendency Framework gained most support in the empirical literature using observational data (Meier, 2022), while it has been less supported by experimental studies.

3. Data

Global Terrorism Data Base. To estimate the effect of terror attacks on risk preferences, we use the Global Terrorism Database (GTD), an open-source dataset covering terror attacks from 1970 to 2022. The data is hosted by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), at the University of Maryland. START is a Department of Homeland Security Center of Excellence and aims at advancing the understanding of the societal cause and consequences of terror. The data is based on publicly available sources, such as newspaper articles, electronic news archives, and other data.

In the GTD, a terror attack is defined as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation." To be included in the GTD, incidents must meet the following criteria (START, 2021, p. 11-12):

The incident must be intentional, involve violence or threats against people or property, and be carried out by non-state actors (excluding state terrorism). Additionally, at least two criteria must be met: (1) the act must aim for a political, economic, religious, or social goal beyond profit motives, (2) it must seek to coerce, intimidate, or send a message to a larger audience, and (3) it must violate international law by targeting non-combatants. We rely on the information of the location and date in the GTD to determine the treatment status of the SOEP respondents.

Socio-Economic Panel. The Socio-Economic Panel (SOEP) contains well-established information on individual risk preferences. First collected in 1984, the SOEP provides a representative panel of individuals living in Germany and their respective households and has been administered to respondents on an annual basis. The SOEP collects comprehensive data on a broad range of individual socioeconomic characteristics, including education, labor market participation, and health status. It currently contains information from approximately 30,000 individuals living in 15,000 households (Goebel et al., 2019).

Outcome. We measure individuals' risk preferences via respondents' stated preferences. Since 2004, respondents in the SOEP provide information on their general risk preferences. Risk preferences are elicited by responses to a single item question "Are you generally a person who is willing to take risks or do you try to avoid taking risks?"

Responses are given on an eleven-point Likert scale, ranging from zero "not at all willing to take risks" to ten "very willing to take risks." Responses to this item are demonstrated to be very predictive for individual's lottery choices and a broad range of risky behaviors (Dohmen et al., 2011). Notably, this measure of individuals' risk preferences is widely used in the economic literature (e.g. Serra-Garcia, 2021; Cobb-Clark, Dahmann, and Kettlewell, 2020; Caliendo, Fossen, and Kritikos, 2010; Meier, 2022; Avdeenko and Eryilmaz, 2021a). In the SOEP, individuals' risk preferences have been surveyed annually since 2008.

Treatment. We use the geo-coordinates of the terror attacks included in the GTD to merge the data to the SOEP. For each individual, we calculate a circle with the radius x kilometres around their residential location. If a terror attack happens within this circle, we code the individual as treated, and zero otherwise. We repeat this with various radii of size x kilometres to elicit the moderating effect of the distance to the terror attack. In the subsequent analyses, we use the radius that is associated with the largest effects.

Other outcomes. We explore the role of emotions for the relationship between terror attacks and respondents' risk preferences. In the SOEP, respondents are asked how frequently they experienced the emotions happiness, anger, sadness, worries, or fear within the last four weeks. Responses to these items are given on an eleven-point Likert-Scale that ranges from one "Very seldom" to five "Very often."

To elicit the effect of terror attacks on risky behaviour, we construct indicators that are equal to one if a respondent owns stocks, is self-employed, is smoking, or participates actively in sport, and zero otherwise.[4] These outcomes correspond to the variants of risky behaviours to validate stated risk preferences in Dohmen et al. (2011).

We include all observations within five years around the terror attack and all observations in the control group. We include only observations that have information on the outcome of interest and the location of the household available.

LexisNexis. The data base of LexisNexis contains the universe of worldwide news. LexisNexis provides this data primarily for businesses with commercial interest.[5] For our analysis, we hand-collected 2,518 newspaper articles about terror attacks covered by the GTD that we include in our analysis. For each article, we have information on

[4] Sport activities prevent diseases such as cardiovascular diseases. Thus, they can be considered a risk mitigating activity.

[5] Access to LexisNexis Research is granted by the Free University of Berlin.

the title, content, newspaper, language, and publication date. Using natural language processing (NLP) methods, we assign media sentiments and media reach to each attack. This allows us to validate our findings and to explore, how news reporting moderates the effect sizes. A detailed description of the news analysis is provided in Appendix A.

Covariate balance. Table 1 displays the covariate balance for our preferred specification.[6][7] We focus on exogenous or predetermined characteristics, such as age, gender, education, migration background, number of children and household size. These covariates are either measured just before the treatment for the treatment group or in the first year of observation for the control group. None of the normalized differences exceeds the threshold recommended by Imbens and Rubin (2015), as shown in Table 1. In fact, most of the normalized differences are below 15 in magnitude. This suggests that including individual and regional fixed effects in the regression is sufficient to account for any imbalances. In fact, for DiD analyses, balanced covariates are not a requirement for identification per se.

Characteristics of terror attacks. Table 2 presents descriptive statistics for the terror attacks in our analysis. These include the count of events, average number of killed or wounded, and average monetary damage. This information is grouped by type of attack, weapon, and target.[8] Most attacks are directed toward infrastructure, with the majority labelled as incendiaries and targeting private citizens or property. On average, terror attacks in our analysis cause 0.23 casualties, 1.05 wounded, and 759,193 USD in damage.

[6] Imbens and Wooldridge (2009) and Imbens and Rubin (2015) argue that t-statistics are not suited to assess the covariate balance between treatment and control group due to the strong dependency on sample size. Therefore, we rely on normalized differences.

[7] In our preferred specification, respondents who experienced a terror attack within a radius of 25km around their residence are included in the treatment group. All other respondents are part of the control group.

[8] Monetary values have been deflated and correspond to 2020 US Dollars.

4. Empirical method

To estimate the causal effect of terror attacks on individuals' risk preferences, we employ a staggered difference-in-differences design. For this, we estimate the following empirical model via OLS:

$$y_{itc} = \alpha_0 + \alpha_1 TerrorAttack_{ti} + \gamma_t + \gamma_c + \gamma_i + \epsilon_{itc}, \tag{1}$$

whereby, y_{irt} corresponds to the risk preferences of individual i, living in county c in year t. Risk preferences are standardized to have a mean of zero and a standard deviation of one in the control group. The indicator *TerrorAttack* is equal to one if the individual experiences a terror attack in their radius, and zero otherwise. The treatment status is absorbing, that is, the individual is treated in the period the attack happens and every period thereafter. Consistent with Brodeur and Yousaf (2022), we keep individuals who are treated multiple times.[9]

We include a vector of year-fixed effects γ_t to account for year specific macro shocks. One example are economic shocks that could be associated with individuals' risk preferences and terror attacks. We also include a vector for county-fixed effects, γ_c, to control for permanent differences across counties that are associated with individuals' risk preferences and terror attacks – for instance, the demographic composition of the county. Similarly, we also include a full set of individual fixed effects, γ_i. These control for permanent differences across individuals. One such example could be education or other (un)observed factors, such as cognitive ability. Notably, we follow individuals, even after they move to other locations after a terror attack. Otherwise, we would lose observations from individuals who are particularly sensitive to these attacks. The term ϵ_{itc} is an unobserved, potentially non-i.i.d., error term. Hence, we cluster standard errors at the individual level (Bertrand, Duflo, and Mullainathan, 2004).[10]

Dose-response relationship. In our analysis, we do not rely on administrative borders to determine the treatment status of the individuals. For instance, if a terror attack

[9] In our main analysis, we focus on what is referred to as a two-way fixed-effects (TWFE) model. However, a large literature emphasizes the potential biases resulting from heterogeneous and dynamic treatment effects in conjunction with staggered occurrences of the treatments (Baker, Larcker, and Wang, 2022). In Section 5.1, we show that our results are robust to these concerns.

[10] All estimations are performed in R using the **fixest** package and the **feols** command within (Laurent Bergé, 2018).

happens in close proximity, but in another administrative unit, we would potentially misallocate the treatment status. Therefore, we use the exact distance between the individuals' household and the terror attack to estimate the dose-response relationship between terror attacks and individuals' risk preferences. The procedure also helps us to improve relative efficiency of the estimates for all subsequent analyses, *e.g.*, the analysis of the mechanisms. For this, we proceed in four steps:

(a) We draw a radius of r kilometers around the individuals' residence.

(b) For each individual and year, we determine whether a terror attack happened in this radius.

(c) Individuals who experience a terror attack in the respective radius will be assigned to the treatment group.

(d) We estimate the empirical model specified in Equation 1 and obtain the estimate of the treatment effect α_{1r} associated with radius r.

We repeat these four steps for all radii from 1 to 125 kilometers, while we estimate the corresponding α_{1r}. This analysis informs us about the moderating effect of the proximity to the terror attack. We choose the radius for which the effect size is maximized to further analyze the effects associated with terror attacks.

Dynamic specification. We are also interested in the dynamics of the treatment effects. We perform an event study analysis to identify whether effects are permanent or transitory, as outlined in Section 2. That is, we estimate the following empirical model:

$$y_{itc} = \beta_0 + \sum_{\tau=-5,\tau\neq-1}^{5} \theta_\tau I(\textit{Event time} = \tau) * \textit{TerrorAttack}_t + \kappa_t + \kappa_c + \kappa_i + \eta_{itc}. \tag{2}$$

Equation 2 largely corresponds to Equation 1. However, in this specification, we are not interested in the average effect of the terror attacks over the treatment periods, but the dynamics of individuals' risk preferences around the terror attack. For this, we include a full set of indicators, one for each relative event time,$I(\textit{Event time} = \tau)$. These are interacted with the indicator for the terror attacks $\textit{TerrorAttack}_{tr}$. The relative event time period 0 corresponds to the year of the respective terror attack. For individuals who experience multiple terror attacks, we set the relative event time back to zero when a new attack happens in their radius. We choose the relative event time –1 as our reference period. Thus the estimates of θ_τ inform us about the dynamics of the treatment effect around the terror attack.

Identification. We rely on the common trend assumption in order to estimate α_{1r} consistently. That is, the conditional population expectation of individuals' risk preferences would have evolved similarly in the treatment and control group in absence of the treatment. Since this assumption involves information on a counterfactual situation, it is not testable. But we provide evidence for the common trend assumption in Section 5.

In our sample, we include all individuals, *i.e.*, treated individuals, never treated individuals and not yet treated individuals. This way, we minimize the risk of underidentification (Borusyak, Jaravel, and Spiess, 2024; Brodeur and Yousaf, 2022).[11] Further, the usage of the full sample reduces the risk of negative weights compared to restricted samples, *i.e.*, only treated and not yet treated observations (Borusyak, Jaravel, and Spiess, 2024).[12] In the robustness section, we show that threats associated with the staggered design or heterogeneous and dynamic treatment effects do not pose a problem for our analysis. For this, we estimate group-cohort average treatment effects, robust to the caveats mentioned before (de Chaisemartin and D'Haultfœuille, 2020). In fact, the estimates from this robustness check are essentially the same as in our main analyses.

An alternative approach, used in the literature, is to compare successful attacks to failed attacks, maximizing comparability among individuals in the treatment and control groups (Brodeur, 2018). However, in our case, this strategy would leave us with only 24 failed attacks for the control group (omitting Berlin, where, in most years, there are multiple attacks), which decreases the reliability of the control group.

Heterogeneous effects. We are also interested in the effects in different population subgroups. For this, we fully interact Equation 1 with indicators for the respective groups. The coefficient that corresponds to the interaction term informs us about the differential effect for the group under consideration.

[11] In an event-study design, not all treatment effects can be point-identified without never-treated observations (Borusyak, Jaravel, and Spiess, 2024).

[12] In event study designs, the DiD can be of opposite sign than the average treatment effect. Including fewer never treated observations increases the relative weight associated with earlier treated observations, worsening the problem associated with negative weights.

Mediation analysis. We are also interested in how far emotions are driving the effect of terror attacks on risk preferences. For this, we first repeat the estimation of the empirical models specified in Equation 1 and 2 for our potential mediators. This shows whether the mediator of interest is actually affected by the terror attacks. In a second step, we provide evidence that the mediators under consideration are associated with individuals' risk preferences. For this, we run a regression of individuals' risk preferences on individuals' frequency of feeling happy, accounting for individual and survey year fixed-effects, in addition to a wide range of individual and household level characteristics.[13] Note that, since potential mediators are also affected by the terror attacks, this could bias the association between the mediator and individuals' risk preferences. To avoid this, we perform this regression in the control group.

[13]This essentially replicates the study of Meier (2022) in our sample.

5. Results

Dose-response relationship. We first estimate the effect of terror attacks on risk preferences for varying radii around respondents' locations, as outlined in Section 4. Figure 2 illustrates the coefficient estimates for each radius, α_{1r}, along with their 95% confidence intervals. The solid orange line represents a locally weighted regression fit.

The results show a negative average effect of terror attacks on individuals' risk preferences. Within the first 25 kilometers, the effects increase in magnitude with distance from the attack. Due to small sample size, the effect estimates for radii below 16 kilometers are statistically insignificant. Beyond 25 kilometers, the effect sizes diminish, converging to zero around 60 kilometers. From approximately 80 kilometers and onwards, the effect sizes are negligible in magnitude and statistically insignificant. Our preferred 25 kilometer cut-off is data driven, as it corresponds to the largest effect size.

Table 3 presents point estimates for radii of 15, 25, 35, and 45 kilometers. The estimates decrease with increasing radii, with point estimates of -0.018 for 15 kilometers and -0.020 for 25 kilometers, compared to -0.011 and -0.010 for 35 and 45 kilometers, respectively. These effect sizes align with effects from the prior literature. For instance, Brodeur (2018) report a 1.8% reduction in employment and a 2.3% decline in earnings following a successful terror attack. Soni and Tekin (2023) find that recent terror attacks reduce the probability of reporting excellent emotional well-being by 5.6 percentage points.

Dynamic treatment effects. The effects emerge immediately following the terror attacks. Figure 3 shows the dynamics of these effects, displaying estimates of θ_τ from Equation 2 with 95% confidence intervals. Notably, the coefficients for the pre-treatment periods provide support for the common trend assumption. All pre-treatment coefficients are close to zero and not statistically significant.

In the year of the attack ($\tau = 0$), risk preferences decrease by approximately 1.3% of a standard deviation. This effect increases to 2% in the following year and gradually converges back to pre-treatment levels. By the fifth post-treatment year, the effect is neither economically nor statistically significant.

5.1. Robustness

Heterogeneity in staggered DiD. Our main specification employs a two-way fixed-effects (TWFE) approach within a staggered DiD framework. While TWFE estimations can be biased in the presence of heterogeneous or dynamic treatment effects (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Baker, Larcker, and Wang, 2022; Sun and Abraham, 2021), we confirm robustness by comparing our main results to estimates derived using the heterogeneity-robust estimator proposed by Sun and Abraham (2021). Figure 4 shows that the estimates from both methods are nearly identical, confirming that our results are not adversely affected by treatment effect heterogeneity.

Omission of Berlin. Berlin is an outlier in terms of attack frequency, with at least one terror attack annually since 2014. This may bias our results due to potential habituation effects or limited post-event periods caused by frequent exposure. In Appendix Table A2, we present results excluding Berlin. The findings remain robust, with the largest effect size still observed at the 25-kilometer radius.

Accounting for the presence of refugees. To account for potential biases related to the local share of refugees, we include the lagged county-level share of refugees as a control variable. Results in Appendix Table A3 confirm that our main findings are robust to this inclusion.

Varying severity of attacks. We analyze the effects of terror attacks with varying levels of severity, focusing on events that result in casualties, injuries, or both. Appendix Table A4 shows that the effects are concentrated in more severe events, with an estimated effect size of 0.31 for attacks involving casualties or injuries – approximately 50% larger than our main estimate.

Target groups. Next, we distinguish between attacks targeting private citizens or property and those targeting other groups. Appendix Table A4 reveals that attacks on private citizens and property drive the results, with an aggregate effect of approximately -0.028.

Risky behaviors. To assess whether changes in stated risk preferences translate into actual behavior, we examine the effects on stock ownership, self-employment, smoking, and participation in sports. Terror attacks increase the likelihood of physical activity by 1.4 percentage points. More severe attacks (*e.g.*, those involving casualties) decrease the likelihood of self-employment by 2.1 percentage points and increase physical activity by 2.4 percentage points (Appendix Table A5).

5.2. Analysis of population subgroups

We explore heterogeneity across population subgroups by interacting our models with group indicators. Results in Table 4 show significant differences. For individuals without migration background, terror attacks reduce risk preferences by 2.5% of a standard deviation, while no effect is observed for individuals with migration background. Similarly, individuals in East Germany experience a 4.2% reduction, compared to a smaller and less significant effect in West Germany. No differences are observed based on income, gender, education, household composition, and age differences.

5.3. Media and Sentiment Analysis

Worse sentiment. Most respondents learn about terror attacks through media coverage rather than personal experience. Table 5 shows that attacks covered with below-median sentiment (*e.g.*, more negative language) reduce risk preferences by 3.2% of a standard deviation, compared to 0.6% for above-median sentiment. Negative sentiment is also associated with longer-lasting effects, with durations extending up to four years (Appendix Figure A4).

Higher coverage. Higher media coverage amplifies the effects of terror attacks. Events with above-median coverage have more severe impacts than those with below-median coverage, as shown in Appendix Figures A4C and A4D. This suggests that both, the extent and tone of media reporting, shape the public's reaction to terror attacks.

5.4. Mediation analysis

Effect on emotions. Using the same empirical strategy, we examine the impact of terror attacks on emotions. Table 6 shows that happiness declines by 1.9% of a standard deviation, with no significant effects on sadness, anger, and worries. The dynamics of happiness (Figure 5B) indicate a peak decline of 2.5% in the second post-event year, followed by a return to baseline.

Association between risk attitudes and happiness. Finally, we investigate the link between risk preferences and happiness. Table 8 shows that a one-standard-deviation increase in happiness is associated with a 4.3% increase in risk preferences. This finding, consistent with Meier (2022), supports happiness as a mediator in the relationship between terror attacks and risk preferences.

6. Conclusion

The disproportionate economic effects of terror attacks point towards psychological mechanisms (Becker and Rubinstein, 2011). This is the first study to systematically investigate the effect of terror attacks on individual risk preferences. For this, we use the GTD – comprising information on the location and date of terror attacks – alongside the SOEP, which provides information on individuals' risk preferences and their location of residence. We implement a staggered DiD, in which we determine the treatment status according to a radius around the residence for each individual in our data.

We find relevant negative effects of terror attacks on individual risk preferences, which decline with the distance of the terror attack to the residence. In our main specification, in which we apply a radius of 25 kilometers, we find that risk preferences decline by about 2% of a standard deviation in response to terror attacks. Our dynamic specification shows that this decline is immediate and transitory. Additional analyses show that this result is robust to various sensitivity checks.

In further analyses, we use the news articles associated with terror attacks. We find that the effect is particularly strong if the terror attack is associated with a very negative sentiment or higher coverage. Further, our analyses reveal that happiness is a channel driving the effects of terror attacks on individuals' risk preferences. This provides additional evidence on the hypothesis of Becker and Rubinstein (2011) that emotions are a key driver in explaining the disproportionate responses to terror attacks.

Overall, our results emphasize the potential role of risk preferences in the large economic effects of terror attacks often found in the literature. For instance, decreasing levels of risk aversion could amplify precautionary saving motives, causing individuals to invest less than in a counterfactual situation and, hence, putting the economy on a sub-optimal growth path. Complementary research indeed suggests that firms downsize their research and development efforts and consumer sentiment decreases in response to terror attacks (Fich, Nguyen, and Petmezas, 2023; Brodeur, 2018). Our results imply that this could be linked to changes in risk preferences.

Although these effects are transitory, they could still yield notable welfare implications. Unlike permanent shifts, temporary changes in risk preferences complicate optimal decision-making, as individuals may regret past choices when preferences revert (Harrison and Ng, 2016).

Future research could examine how terror exposure affects other forms of preferences, such as social preferences or patience. This could further inform how terror attacks alter decision making. Additionally, understanding how terror exposure might shift preferences for public policy, such as support for security-related expenditures or social insurance programs, could provide insight into the long-term policy implications of terror-induced psychological shifts.

7. Tables

TABLE 1. Balance Table

Variable	Mean Treated	Mean Control	Std. Mean Diff.
Cohort	1967.641	1970.086	-0.138
	(0.135)	(0.088)	
Female	0.529	0.501	0.056
	(0.004)	(0.002)	
Married	0.603	0.581	0.045
	(0.004)	(0.002)	
Child in HH	0.382	0.448	-0.135
	(0.004)	(0.002)	
Migration backgr.	0.285	0.362	-0.171
	(0.003)	(0.002)	
Secondary school degree	0.250	0.160	0.209
	(0.003)	(0.002)	
Number obs.	17,080	46,128	

Notes: Table 1 presents the mean values and standard errors (in parantheses)for both the treatment and control groups across various covariates. The third column displays the standardized mean differences between the treatment and control groups. The time-varying outcomes are taken from the relative period '-1' for the treatment group and from the first available observation for the control group.

TABLE 2. Descriptive statistics of terror attacks

Type	Group	Count	Killed (mean)	Wounded (mean)	Damage in $ (mean)
ATTACK	Infrastructure	141	0.000	0.227	970,736
	Armed assault	40	0.825	2.225	207,869
	Bombing	14	0.071	1.500	2,890
	Unarmed assault	11	1.091	6.900	NaN
	Other and unknown	5	0.400	1.800	NaN
WEAPON	Incendiary	142	0.000	0.366	801,210
	Melee	20	0.350	2.105	NaN
	Explosives	17	0.176	1.294	2,890
	Firearms	16	1.625	2.625	NaN
	Other and unknown	12	0.000	0.500	NaN
	Vehicle	4	3.000	14.500	NaN
TARGET	Private Citizens & Porperty	105	0.286	1.606	157,420
	Business	25	0.480	1.520	5,547,292
	Religious Institutions	20	0.050	0.150	3,585
	Other and unknown	18	0.111	0.333	NaN
	Government	17	0.118	0.176	NaN
	Transportation	15	0.000	0.000	NaN
	Police	11	0.091	0.273	477,958
	Total	211	0.227	1.048	759,193

Notes: Table 2 provides an overview of the characteristics of the terror attacks in the sample. For each type and group of attack, the table reports the number of occurrences, the mean number of individuals killed and wounded, and the mean value of property damage in US dollars (monetary values corrected for inflation using base year 2020).

Table 3. Aggregate effect of terror attacks on risk preferences

	Risk Preferences			
	15km	25km	35km	45km
	(1)	(2)	(3)	(4)
Terror Attack	-0.018***	-0.020***	-0.011**	-0.010**
	(0.006)	(0.005)	(0.005)	(0.005)
Observations	325,395	318,696	316,350	315,161
R^2	0.644	0.647	0.648	0.649
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

Notes: Table 3 presents the aggregate effect of terror attacks on individuals' risk preferences. Columns (1) trough (4) display the estimated effects based on treatment radii of 15, 25, 35, and 45 kilometres, respectively. Standard errors are shown in parentheses and are clustered at the individual level. Each regression includes fixed effects for individual, years, and counties. *** p<0.01, ** p<0.05, * p<0.1

TABLE 4. Effects for different population subgroups

	Risk Preferences							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Terror attack	-0.025***	-0.042***	-0.022***	-0.022***	-0.020***	-0.021***	-0.022**	-0.021***
	(0.006)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Terror attack X Migration background	0.028*							
	(0.015)							
Terror attack X West Germany		0.029**						
		(0.012)						
Terror attack X Income $\geq$ 2800 EUR			-0.003					
			(0.010)					
Terror attack X Male				0.006				
				(0.011)				
Terror attack X High school degree					0.003			
					(0.011)			
Terror attack X Children in household						0.006		
						(0.011)		
Terror attack X Married							0.009	
							(0.011)	
Terror attack X Age >52 in 2020								0.005
								(0.011)
Observations	318,696	318,696	301,321	318,696	306,591	315,208	317,337	318,696
R^2	0.648	0.647	0.653	0.648	0.647	0.647	0.648	0.648
Within R^2	0.027	0.023	0.026	0.025	0.026	0.026	0.026	0.026
Person fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Interaction	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Table 4 presents the aggregate effect of terror attacks on an individuals' risk preferences, from a specification including interaction terms to capture differential effects across population subgroups. The first row reports the respective main effect of terror attacks across all specifications, while the subsequent rows show the interaction effect with for different population subgroups. These factors include migration background, region (West Germany), income level, gender (male), educational attainment (high school degree), presence of child in the household, marital status, and age (over 52 in 2020). Row (1) reports the baseline effect of terror attacks, while rows (2) to (9) present results for each interaction term, as described. Standard errors. clustered on the individual level, are shown in parentheses. Each regression is based on the 25km treatment radius and includes fixed effects for years, and counties, all of which are interacted with interaction terms corresponding to the variable of interest, and person fixed effects. *** p<0.01, ** p<0.05, * p<0.1

TABLE 5. Effects for different levels of sentiment, coverage and salience

	Risk Preferences					
	Positive Sentiment	Negative Sentiment	High Coverage	Low Coverage	News Reader	Non News Readers
	(1)	(2)	(3)	(4)	(5)	(6)
Terror attack	-0.006	-0.032***	-0.024***	-0.001	-0.029***	-0.003
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)
Observations	305,615	313,143	312,384	307,165	92,559	85,693
R^2	0.649	0.646	0.646	0.648	0.644	0.621
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓

Notes: Table 5 presents the aggregate effect of terror attacks on an individuals' risk preferences, examining the role of news sentiment and coverage. The rows display the effect of terror attacks, with different splits based on news sentiment and coverage. Column (1) reports results for individuals exposed to terror attacks with above-median (more positive) news sentiment, while column (2) reports results for those exposed to below-median (more negative) sentiment. Column (3) examines attacks with lower (below-median) number of articles, and colum (4) focuses on attacks with lower (below-median) coverage. Column (5) examines the effect of individuals who read the newspaper frequently while column (6) focuses on the non-readers. Standard errors, clustered on the individual level, are shown in parentheses. Each regression is based on the 25km treatment radius and includes fixed effects for individual, years, and counties. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Aggregate effect of terror attacks on emotions

	Anger (1)	Happiness (2)	Sadness (3)	Worries (4)
Terror Attack	-0.006	-0.019***	0.001	0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	281,142	281,005	281,019	280,893
R^2	0.537	0.577	0.533	0.563
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

Notes: Table 6 presents the aggregate effect of terror attacks on the frequency of reported emotions. The columns display the effect of terror attacks on different emotional outcomes. Column (1) reports the effect on anger, column (2) reports the effect on happiness, colum (3) reports the effect on sadness, and column (4) reports the effect on worries. Each regression is based on the 25km treatment radius and includes fixed effects for individuals, years, and counties. Standard errors are shown in parentheses and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Association between individuals' risk preferences and happiness

	Risk Preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Happiness	0.139***	0.045***	0.045***	0.043***	0.043***	0.043***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	124,114	124,114	124,114	124,114	124,114	116,397
R^2	0.015	0.644	0.644	0.650	0.650	0.656
Within R^2		0.002	0.002	0.002	0.002	0.002
Individual fixed effects		✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓
Year fixed effects				✓	✓	✓
Monthly fixed effects					✓	✓
Controls						✓

Notes: Table 8 presents the relationship between individuals' risk preferences and their reported frequency of happiness, estimated using ordinary least squares (OLS) regression. The rows display the coefficient for happiness, controlling for various fixed effects across the models. Column (1) shows the raw association between happiness and risk preferences, while columns (2) to (6) progressively introduce individual, age, year, and monthly fixed effects, as well as additional controls. The controls in column (6) include household income, household income squared, a dummy for unemployment, a dummy for marriage, and a dummy for children in the household. The regression only includes treated individuals based on the 25km treatment radius. Standard errors are clustered on the individual level. ***p < 0.01, **p < 0.05, *p < 0.1.

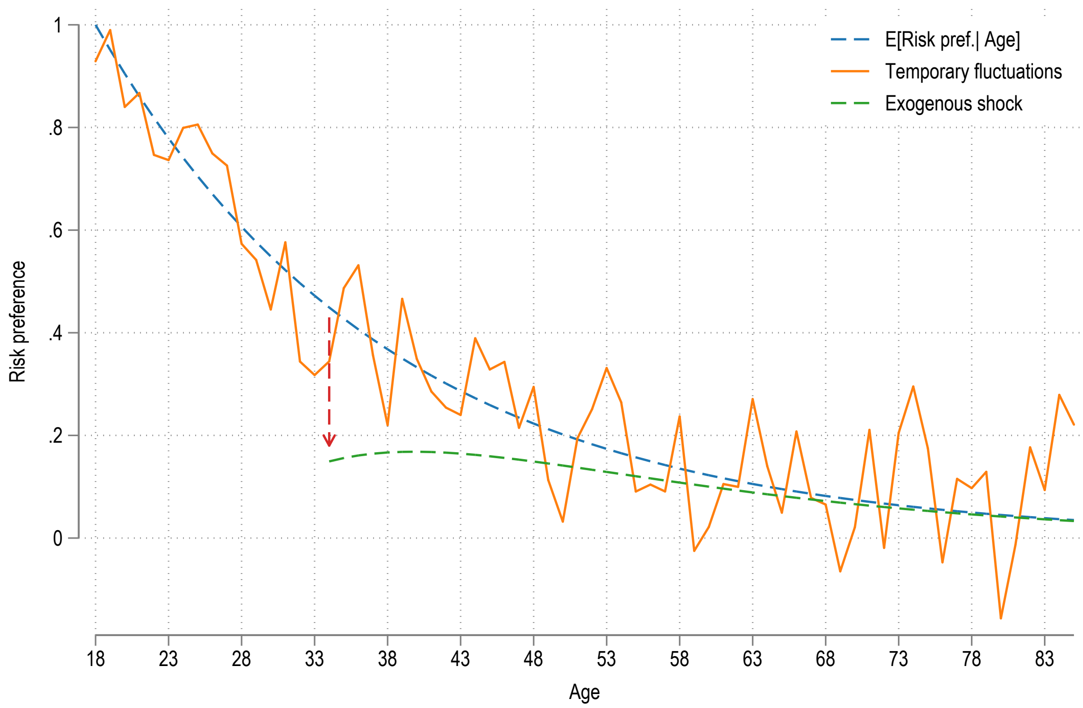
TABLE 8. Association between individuals' risk preferences and happiness

	Risk Preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Happiness	0.161***	0.048***	0.048***	0.046***	0.046***	0.047***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	156,891	156,891	156,891	156,891	156,891	145,903
R^2	0.020	0.662	0.664	0.672	0.672	0.674
Within R^2		0.002	0.002	0.002	0.002	0.002
Individual fixed effects		✓	✓	✓	✓	✓
Age fixed effects			✓	✓	✓	✓
Year fixed effects				✓	✓	✓
Monthly fixed effects					✓	✓
Controls						✓

eftab:risk_happiness presents the relationship betweend individuals' risk preferences and their resported frequency of happiness, estimated using ordinary least squares (OLS) regression. The rows display the coefficient for happiness and risk preferences, while columns (2) to (6) progressively introduce individual, age, year, and monthly fixed effects, as well as additional controls. The controls in column (6) include household income, household income squared, a dummy for unemployment, a dummy for marriage, and a dummy for children in the household. The regression only includes untreated individuals based on the 25km treatment radius. ***p < 0.01, **p < 0.05, *p < 0.1.

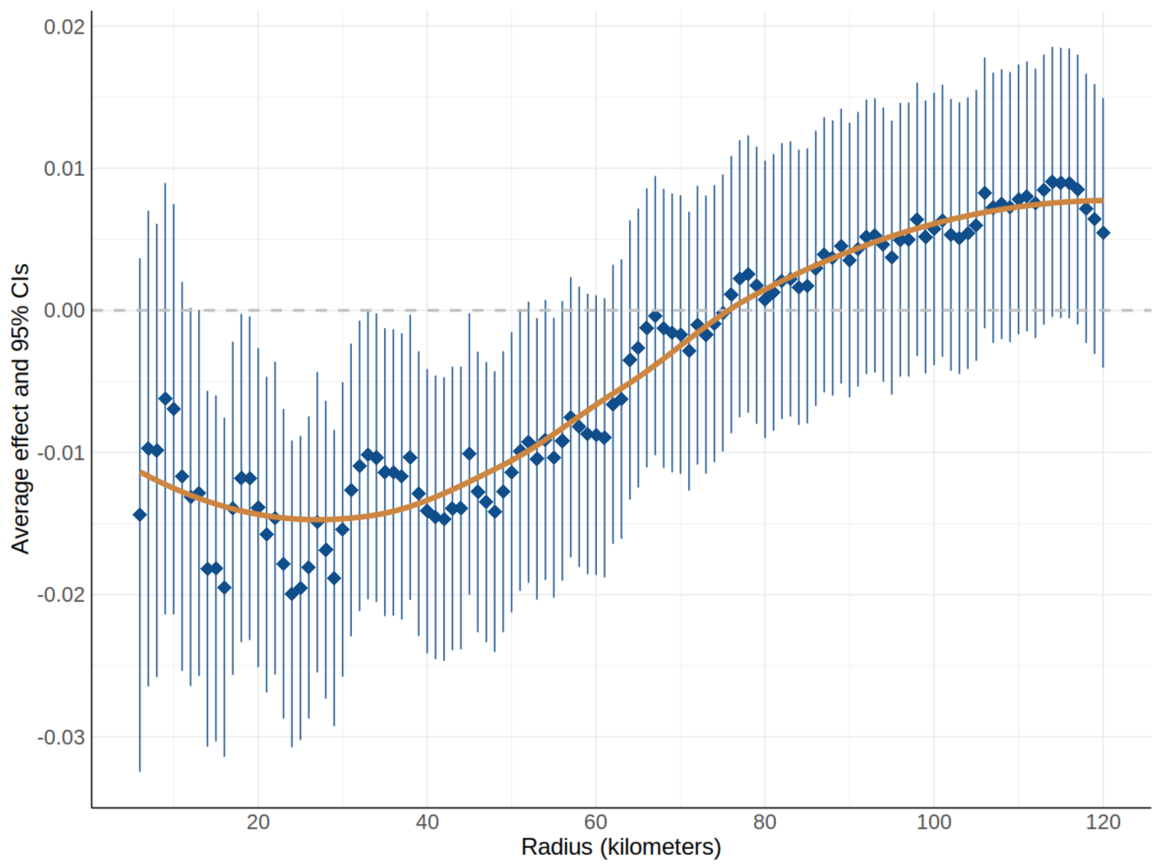
Figures

FIGURE 1. Risk preference over the life-cycle



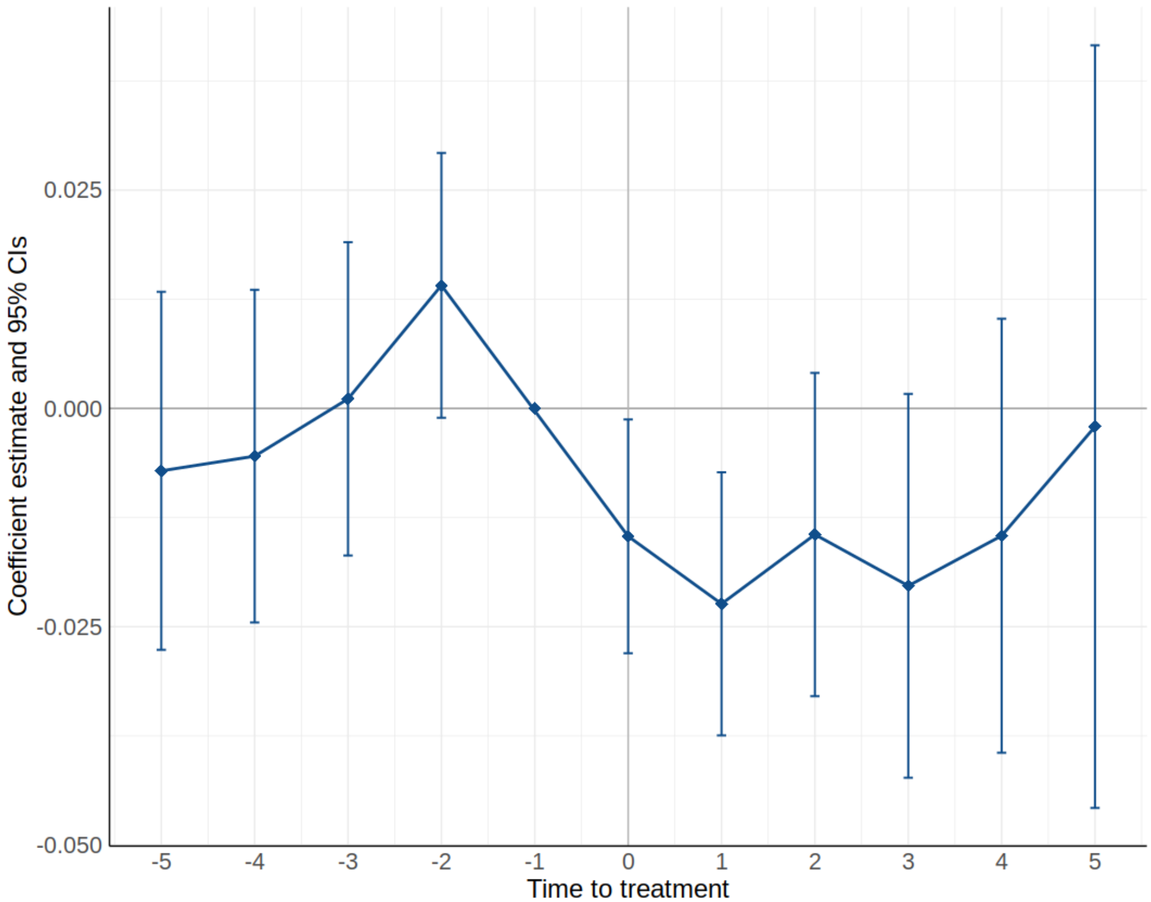
Notes: Figure 1 illustrates the life-cycle of risk preferences. The figure is adapted from (Schildberg-Hörisch, 2018). The dashed blue line displays the life-cycle of risk preferences. The solid orange line represents temporal fluctuations around the life-cycle mean. The dashed green line represents the permanent shift of risk preferences in response to an exogenous shock.

FIGURE 2. Interaction of effect sizes for different radii



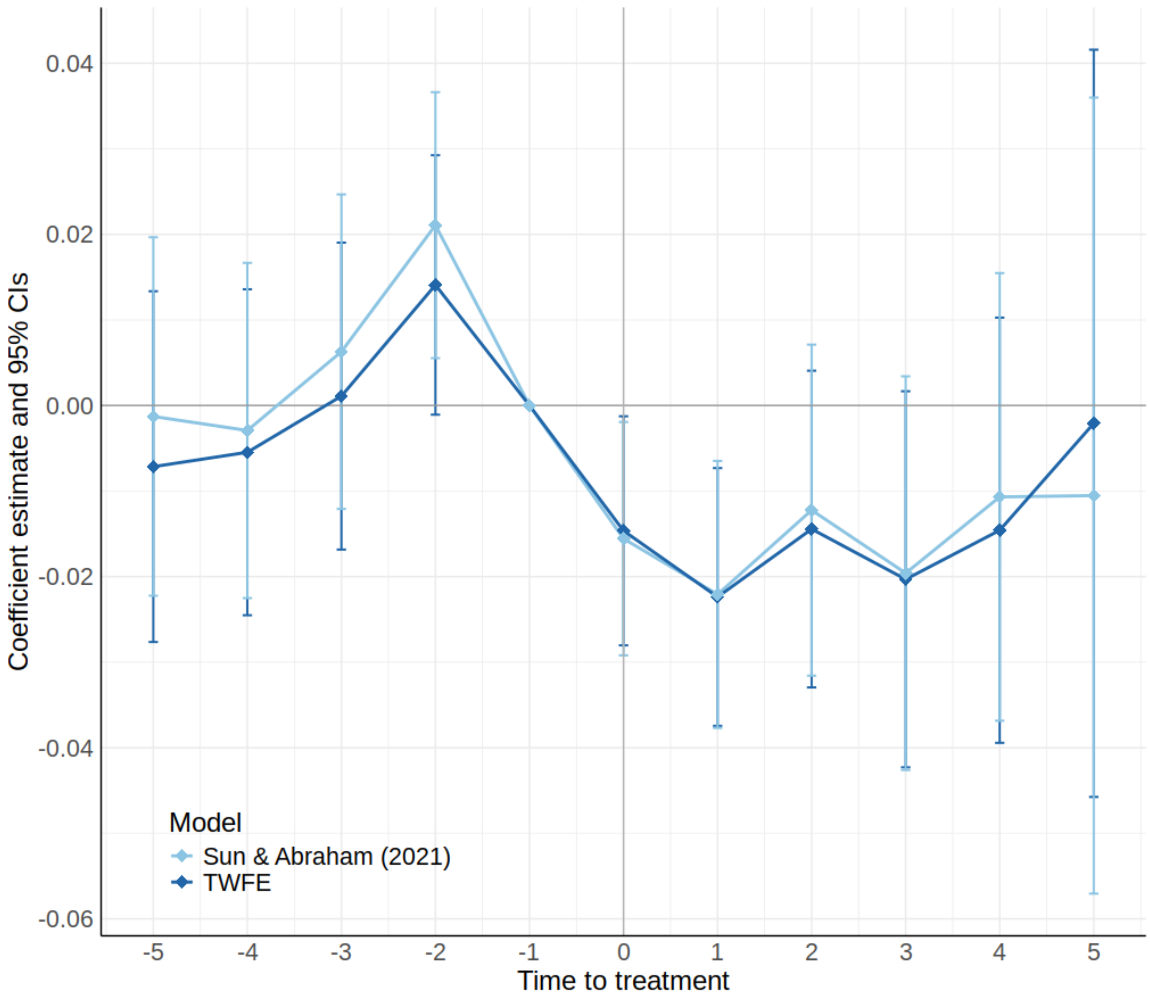
Notes: Figure 2 displays the effect of terror attacks on individuals' risk preferences for each radius. Vertical dashed lines are the associated 95% confidence intervals, based on standard errors clustered on the individual level. The orange line corresponds to the fit, based on a local linear regression of the coefficient estimates on the distance.

FIGURE 3. Dynamic effects of terror attacks on risk preferences



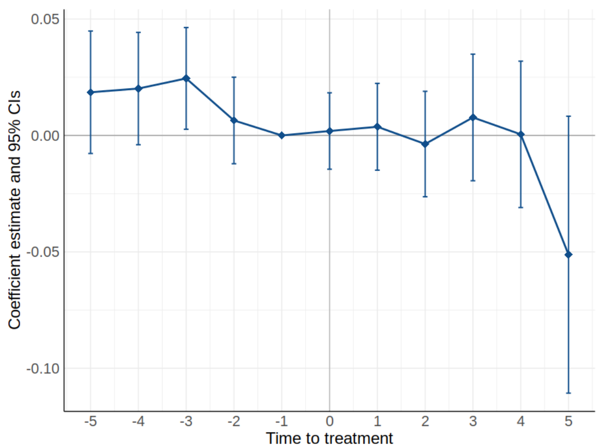
Notes: Figure 3 displays the interaction between an indicator for the treatment group and indicators corresponding to the periods in the event time dimension in the OLS estimation of the empirical model depicted in Equation 2. Negative periods correspond to the pre-treatment periods and non-negative periods to the post-treatment periods. Vertical dashed bars correspond to 95% confidence intervals, based on standard errors clustered on the individual level.

FIGURE 4. Comparison between TWFE and Sun & Abrahams

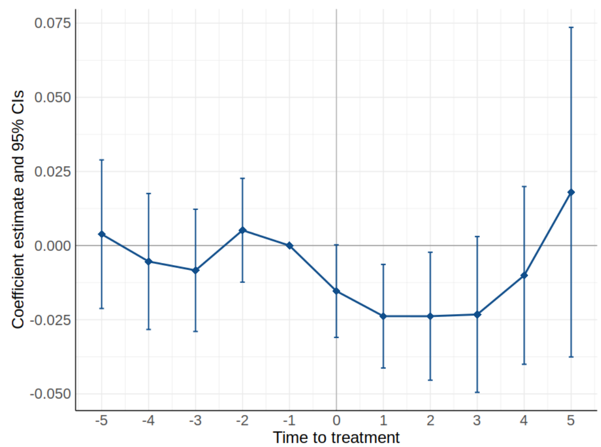


Notes: Figure 4 shows the event-study results both for a TWFE estimation and heterogeneity robust estimates based on Sun and Abraham (2021). Vertical dashed bars correspond to 95% confidence intervals, based on standard errors clustered on the individual level.

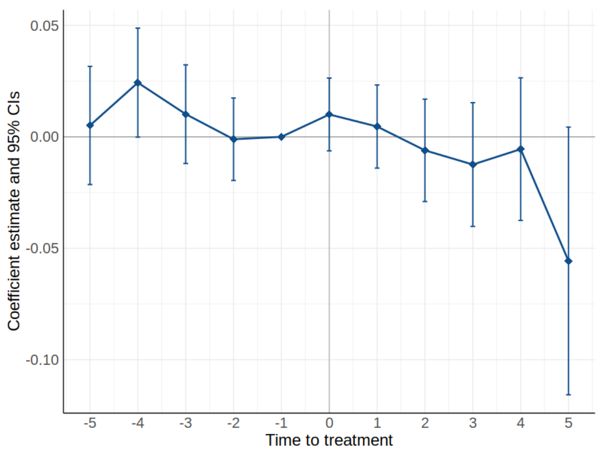
FIGURE 5. The dynamic effects of terror attacks on emotions



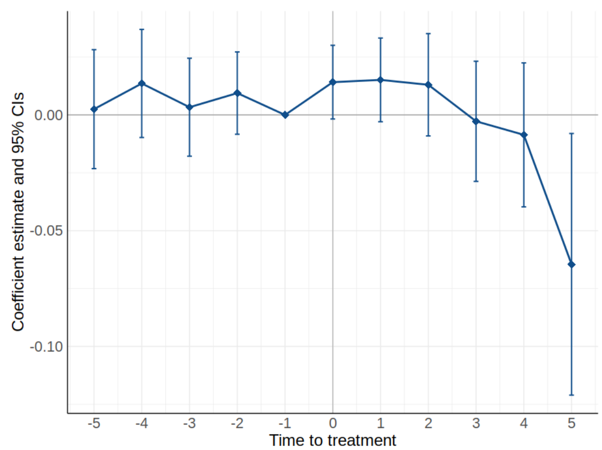
A. Anger



B. Happiness



C. Sadness



D. Worries

Notes: Figure 5A to 5D show the event-study results for the frequency of being angry, happy, sad or worried. The coefficients are based on the estimations of the empirical model, displayed in Equation 2. Figure 5A to 5D display the results for the frequency of feeling angry, happy, sad, and worries, respectively. Vertical dashed bars correspond to 95% confidence intervals, based on standard errors clustered on the individual level.

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Terror and Risk Preferences: Online Appendices

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Daniel Graeber: DIW Berlin - German Institute for Economic Research, IZA and CEPA. **Lorenz Meister**: DIW Berlin - German Institute for Economic Research, Freie Universitaet Berlin, and Harvard University. **Neil Murray**: DIW Berlin - German Institute for Economic Research and Freie Universitaet Berlin. The authors are grateful for valuable feedback from Desmond Ang, Anna Bindler, Christian Krekel, Christian Traxler, participants at the BENA Workshop, the DIW GC Workshop, the Graduate Student Workshop of Political Economy and Rational Choice at the Harvard Department of Government, the 80th Annual Congress of the International Institute of Public Finance, the University of Potsdam, the Socio-Economic Panel, and the University of Trier. The Socio-Economic Panel data can be made available on-site via the research data center of the Socio-Economic Panel group at the DIW Berlin. Scripts for replication are available on request. The authors declare they have no conflict of interest. Any remaining errors are our own.

Appendix A. News Article Compilation

We collected 2,518 newspaper articles that correspond to the terror attacks from our main analysis. The articles were provided by LexisNexis, a comprehensive digital news archive. To identify relevant articles, we filtered the data base by the broad timing and location of each terror incident, and manually selected articles that report about the attack in question. In cases when the results were still too many after filtering, which mostly happened for larger cities, we further filtered by terror-related keywords, *e.g.*, “attack”, “incident”. This procedure yields a rich database of articles, containing the newspaper name, article title, article date, and article content. We assign each article to a specific attack from our main data set, using the unique event ID. We could assign articles to 104 distinct terror attacks. The remaining attacks were so minor that no corresponding press coverage could be found.

Starting with the raw newspaper data set, we filter German articles and translate English ones, as these are most relevant for the sentiment among residents of Germany. This leaves us with 2094 articles. A basic indicator of media coverage is naturally given by the number of articles per attack. Table A1 lists the ten terror attacks with the highest media coverage, showing attack location, date, number of related articles, and news reach. News reach is a measure that weights each article by the reach of the corresponding news outlet, as provided by Zeitungsmarktforschung Gesellschaft (ZMG).

The top 10 out of 104 covered attacks are outlined in Table A1 and represent the most significant terror attacks in recent German history. These include several far-right extremist incidents: the 2016 Munich shopping mall shooting, which resulted in 9 fatalities and 36 injuries; the 2020 Hanau shisha bar shooting, with 11 deaths and five injuries; the 2008 stabbing of Chief Police Officer Alois Mannichl in Passau; the 2019 firearm assassination of politician Walter Lübcke in Wolfhagen; and the 2020 Hamburg attack on a Jewish student with a shovel. Additionally, there was a politically motivated assault by the left-wing perpetrators on AfD politician Frank Magnitz in Bremen (2019). Attacks with Islamist motivations are also noted, such as the 2016 Ansbach suicide bombing by an Islamic State affiliate, injuring fifteen; the 2011 Frankfurt Airport attack, where two American soldiers were killed; the 2016 Würzburg train stabbing of four civilians; and the 2018 Cologne hostage situation and arson by a Syrian refugee.

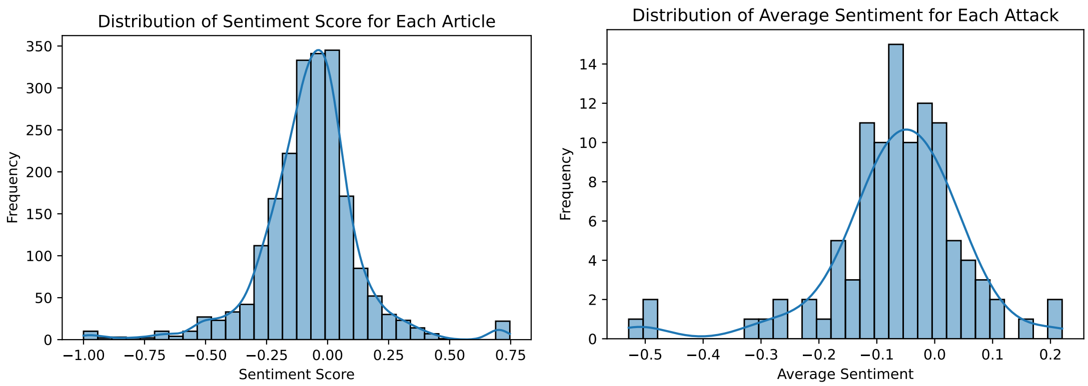
For the sentiment analysis, we proceed by lemmatizing the articles, and removing stop words that do not contain any relevant information. We compute the sentiment

Table A1. Attacks with highest news coverage

Attack location	Month	Year	Articles	News reach
Munich	7	2016	352	538
Passau	12	2008	183	557770
Bremen	1	2019	148	314835
Hanau	2	2020	140	233478
Wolfhagen	6	2019	128	747411
Hamburg	10	2020	105	280550
Frankfurt am Main	3	2011	79	78367
Ansbach	7	2016	73	103401
Würzburg	7	2016	68	256823
Cologne	10	2018	63	17357

Notes: Table A1 presents location, month and year of the terror attack and the number of associated news articles as well as news reach of the ten terror attacks with the higher news coverage. Source: LexisNexis and ZMG.

Figure A1. Distribution of sentiment scores



A. Article sentiments.

B. Attack sentiments.

Notes: Figure A1A displays the distribution of sentiment scores across newspaper articles associated with the terror attacks. Figure A1B displays the distribution of average sentiment scores across terror attack reporting.

for each article and each attack, based on a dictionary that assigns sentiment scores to words. For these computations, we rely on the Python package **germansentiment** (Guhr et al. 2020), which is available at German Sentiment Library. This yields scores that range from -1 (highly negative) to 1 (highly positive). For example, articles with positive sentiment might be expressing relief over a foiled terror attempt, gratitude towards first responders, or hope for a better future. Articles with negative sentiment might be discussing the tragic outcomes, loss, and the horror of the incident. The distributions of sentiment scores per article and attack are plotted in Figure A1. As expected, sentiments tend to be negative. This becomes evident, as most mass of the distribution is to the left of zero, which indicates neutral sentiment. Moreover, the long tails to the left indicate that some news coverage has even very strong negative sentiment.

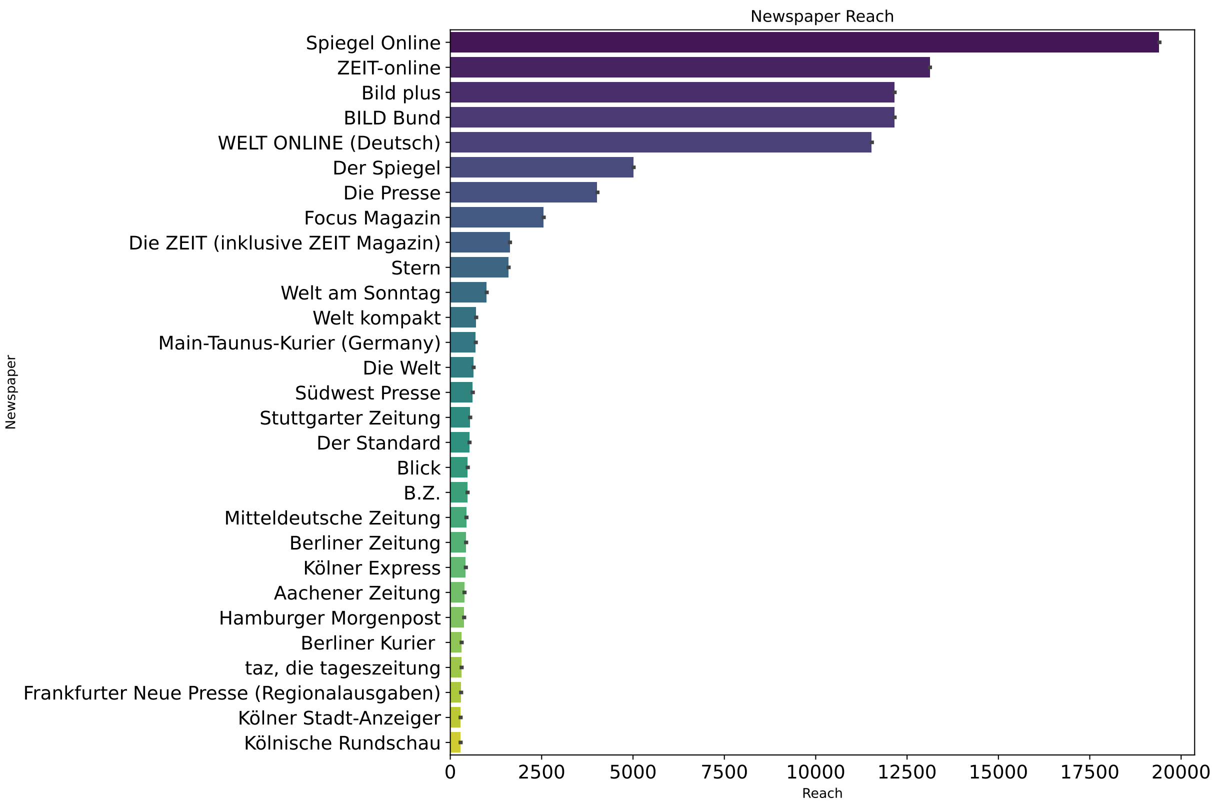
To get a better understanding of the article content, we create a word-cloud that illustrates the most frequent and relevant terms from articles in our database. The result is depicted in Figure A3. Unsurprisingly, words like 'police', 'victim', 'perpetrator', and 'attack' are at the core of the articles, confirming the quality of our dataset.

We conclude this section on the news article collection by providing an overview of indicators we created for each attack:

- **Number of articles** – Contains the number of distinct articles that refer to each attack. Can be used as a measure of salience.

- **News reach** – Contains the size of the audience that could be potentially reached by

Figure A2. Newspaper Reach



Notes: Figure A2 displays the Number of individuals reached by newspaper (in thousands). Source: Zeitungsmarktforschung Gesellschaft der deutschen Zeitungen mbH (ZMG).

reports about the respective attacks. This measure is derived by multiplying each newspaper article by the reach of the outlet and summarizing this number for each attack. Can be used as a measure of salience.

- **Sentiment score (positive/ negative)** – A dictionary-based approach that assigns a sentiment to each attack that ranges from highly negative (-1) to highly positive (+1). Can be used to explore how the general sentiment of an attack moderates the effect of interest.

All of these indicators can be weighted by news reach. For the estimation of heterogeneities, they also may be transformed into categorial variables.

FIGURE A3. Word-cloud of news articles associated with terror attacks in the sample

Notes: Figure A3 displays the most frequent and relevant terms from the newspaper articles on terror attacks, translated from German to English. Source: NexisLexis.

Appendix B. Additional tables

Table A2. Aggregate effect of terror attacks on risk preferences - without Berlin

	Risk Preferences			
	15km	25km	35km	45km
	(1)	(2)	(3)	(4)
Terror Attack	-0.016**	-0.017***	-0.009*	-0.008
	(0.007)	(0.006)	(0.005)	(0.005)
Observations	312,227	305,472	303,127	301,938
R^2	0.644	0.647	0.649	0.649
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

Notes: Table A2 presents the aggregate effect of terror attacks on individuals' risk preferences, excluding observations from Berlin. Columns (1) trough (4) display the estimated effects based on treatment radii of 15, 25, 35, and 45 kilometers, respectively. Standard errors are shown in parentheses and are clustered at the individual level. Each regression includes fixed effects for individual, years, and counties. *** p<0.01, ** p<0.05, * p<0.1

Table A3. Aggregate effect of terror attacks on risk preferences - controlling for the share of refugees

	Risk Preferences			
	15km	25km	35km	45km
	(1)	(2)	(3)	(4)
Terror Attack	-0.023***	-0.021***	-0.010*	-0.011**
	(0.006)	(0.006)	(0.005)	(0.005)
Share refugees (county)	0.004	0.004	0.003	0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	287,037	280,994	279,030	277,997
R^2	0.645	0.648	0.650	0.650
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

Notes: Table A3 presents the aggregate effect of terror attacks on individuals' risk preferences, controlling for the lagged county-level share of refugees. Columns (1) trough (4) display the estimated effects based on treatment radii of 15, 25, 35, and 45 kilometers, respectively. Standard errors are shown in parentheses and are clustered at the individual level. Each regression includes fixed effects for individual, years, and counties. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Aggregate effect of terror attacks on risk preferences for different definitions of terror attacks and target groups

	Risk Preferences				
	Casualty	Wounded	Casualty or Wounded	Target: Private Citizens	Target: Other
	(1)	(2)	(3)	(4)	(5)
Terror Attack	-0.017	-0.028***	-0.027***	-0.028***	-0.006
	(0.013)	(0.008)	(0.008)	(0.007)	(0.007)
Observations	336,202	330,038	329,360	324,470	323,270
R^2	0.639	0.642	0.642	0.645	0.643
Within R^2	0.000	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓

Notes: Table A4 presents the aggregate effect of terror attacks on individuals' risk preferences, considering different definitions of terror attacks and target groups. The rows display the effect of terror attacks across these different specifications. Column (1) reports results for terror attacks with at least one casualty, column (2) reports results for terror attacks with at least one wounded, and column (3) reports results for terror attacks with at least one wounded or casualty. Column (4) focuses on attacks targeting private citizens or porperty, while column (5) presents results for terror attacks with other targets. Each regression is based on the 25km treatment radius and includes fixed effects for individuals, years, and counties. Standard errors are shown in parentheses and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table A5. Aggregate effect of terror attacks on risky outcomes

	Risky Outcome			
	Stocks	Self-employment	Smoking	Sport
	(1)	(2)	(3)	(4)
Terror Attack	-0.004	0.002	-0.004	0.014*
	(0.007)	(0.007)	(0.006)	(0.008)
Observations	296,692	252,981	154,266	173,498
R^2	0.528	0.830	0.869	0.675
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

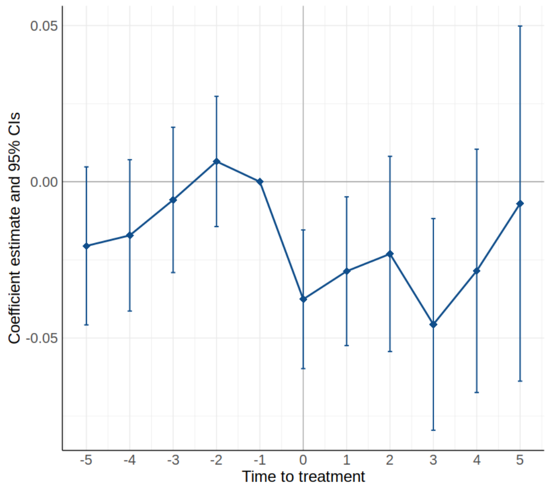
Notes: Table A5 presents the aggregate effect of terror attacks on risky outcomes. The rows display the estimated effects across different risky behaviors. Columns (1) reports the effect on stock ownership, columne (2) reports the effect on self-employment, column (3) reports the effect on smoking behavior, and column (4) reports the effect on participation in active sports. Each regression is based on the 25km treatment radius and includes fixed effects for individuals, years, and counties. Standard errors are shown in parentheses and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table A6. Aggregate effect of terror attacks on risky outcomes (at least one casualty or wounded)

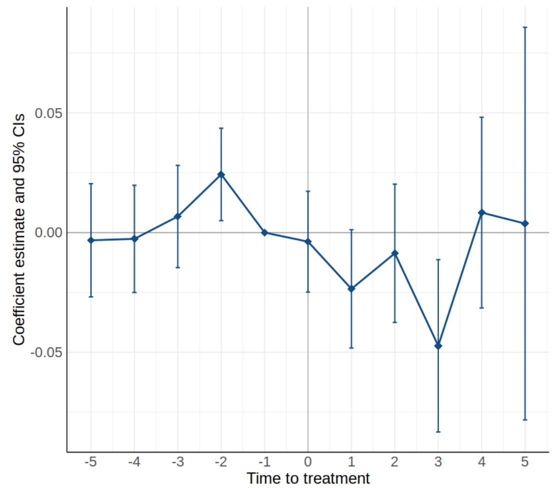
	Risky Outcome			
	Stocks	Self-employment	Smoking	Sport
	(1)	(2)	(3)	(4)
Terror Attack	-0.013	-0.021**	-0.008	0.024*
	(0.011)	(0.010)	(0.008)	(0.013)
Observations	307,505	263,772	160,564	180,178
R^2	0.523	0.825	0.864	0.667
Within R^2	0.000	0.000	0.000	0.000
Person fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓

Notes: Table A6 presents the aggregate effect of terror attacks with at least one casualty or wounded individual on risky outcomes. The rows display the estimated effects across different risky behaviors. Columns (1) reports the effect on stock ownership, columne (2) reports the effect on self-employment, column (3) reports the effect on smoking behavior, and column (4) reports the effect on participation in active sports. Each regression is based on the 25km treatment radius and includes fixed effects for individuals, years, and counties. Standard errors are shown in parentheses and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

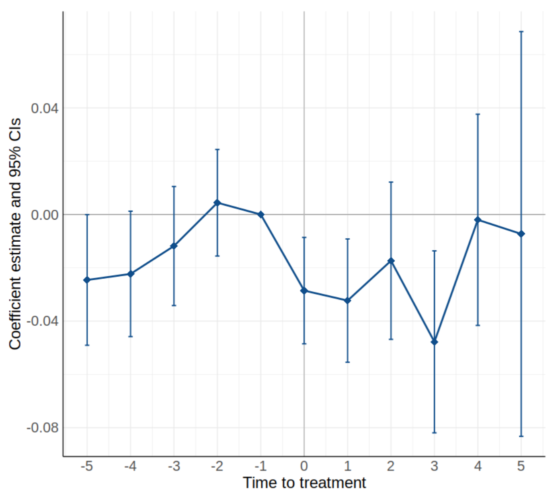
Appendix C. Additional figures



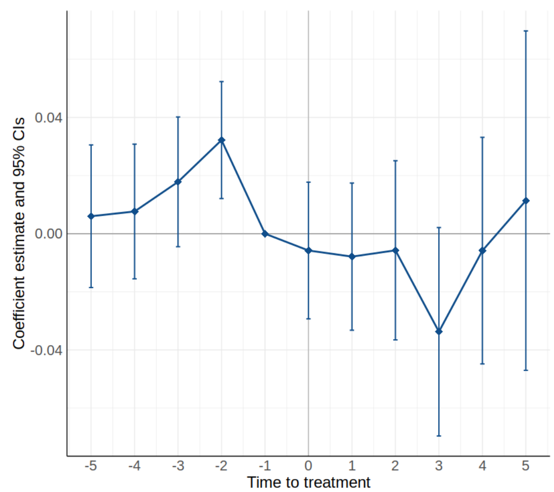
A. Worse sentiment



B. Better sentiment



C. Higher media coverage



D. Lower media coverage

Figure A4. Effect heterogeneity by news sentiment and coverage.

Figure A4 shows event-study graphs on the effect of terror attacks on the willingness to take risks for various subsamples. Panel A contains the sample of individuals who were exposed to terror attacks with below-median news sentiment, i.e. more negative sentiment. Panel B corresponds to the sample exposed to above-median sentiment, i.e. more positive sentiment. Panel C corresponds to attacks that were covered by a lower (below-median) number of articles. Panel D corresponds to attacks that were covered by a higher (above-median) number of articles.

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