Journal of Development Economics 155 (2022) 102817

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular Article

Does terrorism make people pessimistic? Evidence from a natural experiment

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ARTICLE INFO

JEL classification:
I12
D74
H56
C90
P16

Keywords:
Terrorist attacks
Pessimism
Low-casualty
Africa

ABSTRACT

This paper uses a natural experiment to estimate the causal impact of low-casualty terrorist attacks on pessimistic beliefs in Africa. Distinct from fear, pessimism has been found to hinder optimal economic decisions and well-being. By comparing survey responses of people interviewed in the same area immediately before and after a terrorist attack, we find that terrorism increases pessimism about future living conditions by 11 percentage points. The effect is not driven by the direct damages of attacks or people's expectations of the national economy, and is stronger for attacks targeting religious figures and among respondents living in rural areas. Further analysis suggests that this effect tends to shift people to more accurate beliefs. Our results thus show that even low-casualty terrorist attacks have a substantial impact on people's beliefs.

1. Introduction

The recent decade has witnessed a dramatic increase in terrorist activities. In Sub-Saharan Africa (SSA), for example, the number of terrorist attacks has increased fivefold since 2008.[1] The majority of this increase comes from attacks resulting in low numbers of casualties.[2] Despite the frequent occurrence, however, what motivates such low-casualty attacks and their economic impacts on society remain largely unknown. In particular, if sewing terror is the key objective of terrorists, do low-casualty attacks help achieve this goal? If so, what is the channel through which low-casualty attacks exert impact, given the limited direct damage?

Research suggests that terrorists can leverage elements of our innate psychology to spread terror (e.g., Becker and Rubinstein, 2011; Schlenger et al., 2002). Brodeur (2018) documents that terrorist attacks can negatively affect consumer sentiment in addition to causing direct physical damage. Metcalfe et al. (2011) and Clark et al. (2020) also stress the negative psychological impact of terror acts on people's well-being. While insightful, these studies mainly focus on terror attacks with relatively large numbers of casualties, such as the 9/11 attack in New York and the 2013 Boston Marathon bombing. Whether low-casualty terror acts have similar psychological impacts remains a question.

This paper evaluates the causal impact of low-casualty terrorist attacks on people's pessimistic views and provides suggestive evidence on the associated economic loss. Pessimism, a psychological trait defined as a lack of hope for the future, has been linked to increased mortality risks (Peterson et al., 1988; Anthony et al., 2016) and various mental health issues (Peterson et al., 1998; Seligman, 2000). Distinct from fear, a common emotion which often leads to preventive actions that minimize perceived risks (e.g., Leventhal et al., 1965; Krisher et al., 1973; Ruiter et al., 2001), pessimists tend to believe that any actions taken are unlikely to have a material impact on future outcomes. Therefore, they are likely to make sub-optimal household decisions (Puri and Robinson,

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[1] According to the Global Terrorism Database (GTD), the number of terrorist attacks in SSA was 380 in 2008. In 2018, this number increased five times over, reaching 2172 attacks. Terrorism has been increasing in Africa due to its regional features, such as religious fundamentalism, ethnic tensions, and political instability (Asongu and Nwachukwu, 2017; Ajide, 2021; Asongu et al., 2021). According to the Global Terrorism Index published by the Institute for Economics and Peace (2019), the economic impact of terrorism in SSA is estimated to be 12.17 billion USD in 2018, accounting for 37% of the global total.

[2] For example, 68% of the terrorist attacks during 2008–2018 involved fewer than five casualties. Of those (68%) attacks, a further 42% involved zero casualties. These calculations are based on the GTD database.

https://doi.org/10.1016/j.jdeveco.2022.102817
Received 14 February 2020; Received in revised form 27 December 2021; Accepted 5 January 2022
Available online 10 January 2022

2007), reduce risky investments (Bonaparte et al., 2017) and decrease entrepreneurial activities (De Meza et al., 2019).[3] Pessimism thus has a profound negative impact on people's well-being and economic development (Frey and Stutzer, 2000).

Estimating the causal effects of terrorism on the extent to which people feel pessimistic is challenging, mainly because targets of attacks are not randomly selected. The perpetrators may plan attacks strategically to undermine state legitimacy (Condra et al., 2018), facilitate terrorist recruitment (Bueno de Mesquita and Dickson, 2007), and maximize government concessions (Pape, 2003). The difficulty of controlling for all the confounding factors that may be associated with the psychological responses in a region further hinders a clean causal interpretation of the evidence (e.g., Schlenger et al., 2002; Bleich et al., 2003; Hobfoll et al., 2006). For research that solely relies on post-attack surveys, respondents' behavioral biases (e.g., cognitive dissonance) make the task even more challenging (e.g., Schuster et al., 2001; Galea et al., 2002). In several recent studies, scholars have advanced this literature by employing various innovative strategies to isolate plausibly exogenous variation in the degree of attack exposure (e.g., Getmansky and Zeitzoff, 2014; Hirsch-Hoefler et al., 2016). They add credibility to the estimated treatment effects by comparing the psychological responses of those more exposed to terrorist attacks to those with less attack exposure. However, a drawback of these empirical strategies is that they cannot be used to investigate the overall effects of terrorism on people's psychological responses unless one assumes that terrorist attacks have no impact on those with relatively less exposure (Jakiela and Ozier, 2019).

We circumvent these endogeneity issues by using a quasi-experimental setting in which terrorist attacks occurred in the same regions during the fieldwork of a large-scale representative survey, Afrobarometer. This generates plausibly exogenous variation in exposure to terrorism for nearly 1800 respondents in five African countries during 2008–2013, as some respondents were interviewed a few days before the attacks while others in the same region were interviewed immediately after the attacks. We include the sub-national region by survey-wave fixed effect to eliminate the time-invariant factors as well as the time trend at the regional level that may confound our results. We are essentially comparing individuals living in the same regions and exposed to the same attacks. In addition, since Afrobarometer provides finely grained information on respondents' interviews, we conduct our empirical tests across different time windows, such as 15 and 3 days before and after the attacks, and further confine our analyses to those interviewed by the same enumerators. Balcells and Torrats-Espinosa (2018) and Depetris-Chauvin et al. (2020), among others, have used similar empirical designs to study electoral consequences and nation building following terror attacks and national football matches, respectively.

Using this identification strategy and comparing individuals interviewed within 15 days before and after each attack in the local region, we find terrorism makes people 8 percentage points more likely to express pessimistic views of their future living conditions, a 31% jump relative to the pre-attack average. When we focus on individuals interviewed within 3 days immediately before and after the attacks, the size of this effect increases to 11 percentage points (69% of the pre-attack average), revealing a clear discontinuity in people's pessimistic views at the time of the attacks. Moreover, this effect remains robust and quantitatively similar (13 percentage points) when we focus on terror attacks with zero casualties. We further show that this effect is not driven by the direct physical impact of terrorist attacks, nor by individuals' views on the prospects of the national economy.

Our empirical strategy relies on the random overlap between the timing of terrorist attacks and the timing of Afrobarometer interviews in the same regions. While it is difficult, if not impossible, to imagine that Afrobarometer and the terrorist organizations may coordinate their actions, the implementation of the fieldwork could be different in the presence of terrorist attacks, which may result in systematically different samples of respondents accessed before and after the attacks. To address this concern, we conduct the following exercises. First, we note that Afrobarometer randomizes selections at all stages of sampling. In particular, enumerators at the interview stage randomly pick their starting points in the primary sampling areas and then follow random walk patterns to select households to interview. Therefore, the overall random sampling design of the survey is unlikely to be affected by the low-casualty attacks during the implementation stage in our sample. We are reassured of this by the robustness of the results when we only focus on areas distant from the attacks and attacks with zero casualties, as such attacks are especially unlikely to affect Afrobarometer's fieldwork in these cases.

Second, we demonstrate that people interviewed before and after terrorist attacks are not systematically different in their observable demographics, including age, gender, level of education, and employment status. But the respondents interviewed after terrorist attacks are more likely to be from rural areas and seem to be more distant from the attacks than the pre-attack respondents when we focus on a narrow window of three days around the attacks. It is possible that since attacks tend to target urban places, individuals living in such areas may stop responding to survey requests immediately after the attacks due to the potential negative psychological shock. However, such a possibility would only lead to an underestimation of the terrorism impact, since these potentially missing respondents are more likely to hold pessimistic views. We find that the larger impact in rural areas is possibly due to the lack of public security infrastructure. In any event, we control for these characteristics in the regressions.

In addition, we show that the post-attack respondents are not different from the pre-attack ones in terms of trust towards others, cooperativeness during the survey, or the number of attempts made by the interviewer to reach each respondent. Another concern is that our variable of attack exposure may capture the effects of other concurrent events that are associated with the degree of pessimism felt by people. Although we rely on the clear discontinuity pattern within a short period of time before and after the attacks for inference, it is still possible that a spurious correlation may exist, driven by the factors underlying terrorist attacks and local pessimism. To address this concern, we randomly assign the attack dates within the attack-overlapped survey windows and re-estimate the terrorism impact for 1000 times. We find that the placebo coefficients are distributed around zero and the true estimate lies far outside the 99% confidence interval. This suggests that our results are unlikely to be a simple reflection of other concurrent mechanisms.

We also conduct a large number of robustness checks on our main results, including using alternative measures of the treatment and outcome variables, alternating the time windows around the attacks for estimations, adding more individual covariates, making different assumptions on the variance-covariance matrixes, and arbitrarily dropping terrorist attacks from analyses. Our results remain qualitatively unchanged, if not stronger. In an extension, we discover that the effect is more pronounced when the attacks are directed against religious leaders or institutions. This may not be surprising given that nearly all respondents in our sample are religious and 85% of them regard religion as "very important." We do not find other statistically meaningful results in the heterogeneous analyses across other types of attacks and targets.

We discuss the implications of the results following two streams of research. First, guided by the literature on motivated beliefs (e.g., Bénabou and Tirole, 2016), we engage in an extension to explore how the impact on pessimism may relate to the accuracy of beliefs. We use the feature of the repeated Afrobarometer surveys in which respondents

[3] Relatedly, literature finds that fatalistic belief is associated with lower demand for credit in rural Ethiopia (Bernard et al., 2011). A recent study by Akesson et al. (2020) shows that believing that COVID19 is more infectious makes people less optimistic and less willing to take preventive measures.

in wave T are asked their beliefs about future living conditions in the next 12 months, while in the next wave $T+1$, respondents are asked to evaluate their current living conditions compared to 12 months ago. Even though the time between the two waves are much longer than 12 months, and the samples of respondents have changed in different waves, the country-level averages tend to suggest that the countries in our sample mostly lie in the optimistic domain. Adding the treatment effect of terrorism on pessimism to the ex ante mean belief, the country averages remain in the optimistic domain, but are closer to the 45-degree line. This thus suggests that the impact of terrorism on pessimism is pushing people to more accurate beliefs.

Second, we investigate whether the change in pessimistic beliefs matters for economic outcomes. Because there is a lack of data on the economic variables with high-frequency variation, we cannot use our baseline identification strategy. Our correlation analyses here, therefore, may be subject to biases of omitted variables and reverse causation. We thus caution our readers to be careful when interpreting our results here. Firstly, using Afrobarometer, we document that pessimism towards future living conditions is positively associated with unemployment and negatively correlated with years of schooling. These relationships are robust to the inclusion of individual characteristics and enumeration area fixed effects. The economic magnitude of these estimates is nontrivial. Using our most restrictive model, for example, a one-ordinal-scale increase in the degree of pessimism is associated with a two percentage points increase in the probability of being unemployed. Secondly, we construct measures of economic development using data on night light density and link them to the average pessimism at the level of enumeration areas. We find that pessimism is also negatively correlated with night light density. Thirdly, we find that local pessimism at the enumeration level is negatively correlated with the availability of many infrastructures in the enumeration area, such as electricity grids, piped water, and sewage system. Although the magnitude of the impact of terrorist attacks on pessimism is on average twice the size of our estimated correlation coefficients between pessimism and local infrastructures, it is important to stress that this comparison should not be taken at face value. As emphasized above, these conditional correlations are likely not causal.

To quantify the economic cost associated with pessimism, we perform a back-of-the-envelope, suggestive analysis combining our estimates with the elasticities between night light density and GDP growth estimated by Henderson et al. (2012) and Chen and Nordhaus (2015). It is worth noting that these quantifications are rather speculative. At the risk of over-extrapolation, we show that the economic cost associated with each attack roughly ranges from 90 to 157 million US dollars. It is important to reiterate that this estimate on the economic cost of pessimism cannot be taken at face value. While the cost estimates rely on the elasticities between night light density and GDP growth over the long run (Henderson et al., 2012; Chen and Nordhaus, 2015), our identification of terrorism's impact on pessimism is limited to the short-term (e.g., within 15 and 3 days after the attacks). We thus caution our readers to bear this caveat in mind when interpreting our findings.

This article relates to the literature on the economic costs of terrorism.[4] While the majority of the research focuses on catastrophic terror events, such as the 9/11 attack in New York (e.g., Schlenger et al., 2002; Metcalfe et al., 2011), the 2013 Boston marathon bombing (e.g., Clark et al., 2020), those perpetrated by the terrorist group Euskadi Ta Astanan in Spain (e.g., Abadie and Gardeazabal, 2003; Balcells and Torrats-Espinosa, 2018), and those committed by the Al-Aqsa Intifada in Israel (e.g., Bleich et al., 2003), there is little research that studies the impact of low-casualty terrorist attacks. Our paper suggests that the low-casualty terror acts in Africa also impose a substantial amount of psychological stress and economic costs, and thus provides an explanation for why such attacks are increasing dramatically.

In particular, our paper is closely related to Metcalfe et al. (2011). In their innovative study, Metcalfe et al. (2011) employ a similar empirical design and find that the September 11 attacks caused a significant amount of mental distress in people living in the United Kingdom. Our article is distinct from theirs in three important ways. First, we focus on a different aspect of mental attitudes, pessimism, which has been linked to numerous economic activities. Second, we look at the direct psychological impact of terrorism on people exposed to terrorism (i.e., living in the same regions where terrorist attacks occurred), while Metcalfe et al. (2011) examine the equally important spillover effects of terrorism. Third, Metcalfe et al. (2011) examine the impact of the September 11 attacks, while our study focuses on multiple, less catastrophic terrorist events (in terms of casualties) which arguably have more generalizability in other similar contexts.

This paper also connects to the psychology literature that examines people's responses after terrorist attacks (e.g., Schuster et al., 2001; Galea et al., 2002; Schlenger et al., 2002; Silver et al., 2002; Bleich et al., 2003). While this research has produced tremendous insights, it uniformly focuses on one catastrophic event, the September 11 attack, and fails to account well for the omitted variable bias and the non-randomness in the selection of attack targets. We advance this literature by causally estimating the impact of terrorism on people's psychological response, across a number of terrorism events.[5]

The rest of the paper is organized as follows. Section 2 presents the key information on terrorism in Africa, describes the data, shows the summary statistics of the key variables, and discusses our identification strategy. Section 3 estimates the impact of terrorism on people's pessimistic views, examines alternative interpretations, and conducts robustness checks and heterogeneous analyses. Section 4 discusses the economic and behavioral consequences of pessimism, and Section 5 concludes.

2. Data and identification strategy

2.1. Data

The data on terrorist attacks are from the Global Terrorism Database (GTD), developed by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). It is the most comprehensive open-source database of terrorist attacks around the world. For each terrorist attack, we obtain detailed information, including location, date, target, weapons, casualties, etc.[6] In panel A of Fig. 1, we plot the number of terrorist attacks by year over 1970–2018 for Sub-Saharan African countries and for the countries in our sample, respectively. Overall, Africa has observed steady growth in terrorist activities in the past decades due to its regional features, such as religious fundamentalism,

[4] These include the effects of terrorism on national income and growth (Abadie and Gardeazabal, 2003; Blomberg et al., 2004; Eckstein and Tsiddon, 2004), tourism (Enders and Sandler, 1991; Enders et al., 1992; Fleischer and Buccola, 2002; Drakos and Kutan, 2003), foreign direct investment (Abadie and Gardeazabal, 2008; Enders and Sandler, 1996), savings and consumption (Fielding, 2003; Eckstein and Tsiddon, 2004), allocation of investments (Abadie and Gardeazabal, 2003; Lacker, 2004; Chen and Siems, 2007; Eldor and Melnick, 2004), foreign trade (Blomberg et al., 2004), and urban economy (Glaeser and Shapiro, 2002; Abadie and Gardeazabal, 2008).

[5] We also add to the broader literature which shows that violence affects individual's economic preferences in conflict-affected regions. For example, exposure to civil conflicts in Burundi affects individuals' social and risk preferences (Voors et al., 2012), and the postelection crisis in Kenya increases individual risk aversion significantly (Jakiela and Ozier, 2019). Callen et al. (2014) show that the impact of trauma on risk and certainty preferences is more pronounced for the individuals exposed to violence in Afghanistan.

[6] As defined by the GTD, terrorism is "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."

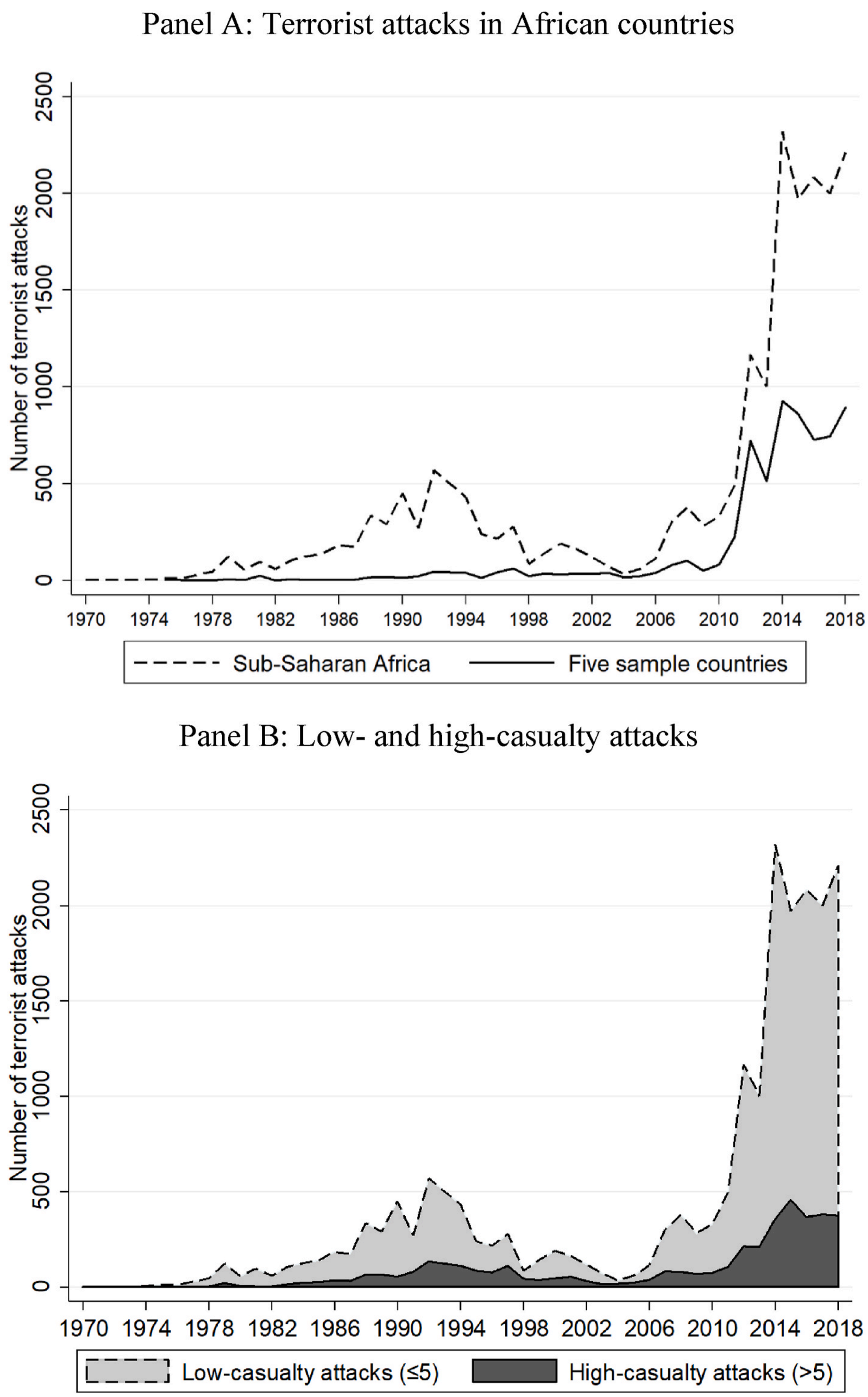

Fig. 1. Terrorist Attacks in Africa. *Note*: Panel A of this figure plots the number of terrorist attacks over 1970–2018 for Sub-Saharan Africa and for the countries in our sample (Kenya, Mali, Nigeria, Tunisia, and Uganda), respectively. Panel B breaks up the total number of terror attacks in Sub-Saharan Africa by the number of casualties. Low-casualty attacks refer to those with five or less deaths and injuries. Data source: Global Terrorism Database.

ethnic tensions, and political instability (Asongu and Nwachukwu, 2017; Ajide, 2021; Asongu et al., 2021). There are also a large number of attacks in the five countries in our sample. In particular, terrorist activities increased dramatically during our sample period 2008–2013. When plotting high- and low-casualty attacks separately in panel B, we find that the majority of the increase was driven by the latter.

Africa is home to several terrorist organizations, such as al-Shabaab in Kenya, the Karamojong Warriors in Uganda, Tuareg extremists in Mali, Boko Haram in Nigeria, and al-Qaeda in Sudan. The fact that these organizations originate from Africa poses identification challenges to the studies on terrorism using cross-sectional data (Venieris and Gupta, 1986; Barro, 1991; Alesina and Perotti, 1996; Alesina et al., 1996), as the factors that lead to terrorism in Africa may also determine the socio-economic outcomes. Moreover, the attacks are not randomly placed. They are often selected based on various local conditions.

By using a natural experiment where the attacks occurred while a series of representative surveys were being conducted in the same regions, we identify the causal impacts of terrorist attacks on people's pessimistic views by comparing the respondents interviewed immediately before one attack with those who lived in the same region but were interviewed immediately after that same attack. This discontinuity nature helps eliminate the concern of local confounding factors.

To conduct our study, we combine GTD with survey data from Afrobarometer, a series of large-scale surveys covering many African countries. Starting from 1999, the Afrobarometer surveys have been conducted in seven waves across Africa. In each country, a nationally representative sample of either 1200 or 2400 respondents of voting age was randomly selected. We exclude the last two waves (2016–2019) since they did not contain information on respondents' pessimistic views.

We match the terrorist attacks data from GTD with the individual survey data from Afrobarometer, using the detailed information on respondents' locations and the dates of each interview. We obtain a sample of individuals who were interviewed while the terrorist attacks took place in the same regions. To ensure that we are able to compare individuals interviewed immediately before one terrorist attack occurred in a region with those from the same region but were interviewed immediately after that attack, we focus on the regions where there were interviews conducted within 30 days before and after the same attack.

In total, we obtained nine region-wave cells where the attacks and surveys overlapped. They are from five countries in the years during 2008–2013 and cover 1783 individuals, of which 876 were interviewed before the attacks and 916 after. For 90% of them, the interviews were conducted within 15 days before or after the attacks happened in the same regions. The timing of interviews relative to local attacks is illustrated in detail in Fig. A1 in the Appendix. Overall, 17 terrorist attacks took place in these nine region-wave cells. Three cells were exposed to multiple attacks within a few days.[7] Detailed information about these nine region-wave cells is presented in Table 1, including country, region, number of attacks, date of the first attack, number of casualties, length of time and number of individuals covered by the survey before and after the attack in the local region, and number of interviewers in each region-wave cell.

2.2. Key variables

We measure individuals' exposure to terrorism in several ways. First, we construct a dummy variable, *post*, which equals one for individuals who were interviewed on or after the date when terrorist attacks occurred in the same region, and zero if they were interviewed before the attacks. For the three region-wave cells where multiple attacks took place consecutively, *post* equals one after the date of the first attack, indicating that individuals had been exposed to at least one attack in the local region at the time of survey. Table A1 shows that, on average, 51% of the respondents in our sample were interviewed after attacks occurred in the local region.

To complement the first measure, we also construct *intensity* to measure the number of attacks that occurred in the local region at the time of the interview. It is zero if the individuals were interviewed before the local attacks happened. As emphasized in the literature, the level of lethality is relevant in understanding the impact of terrorism (Kibris, 2011; Getmansky and Zeitzoff, 2014). We thus employ the record of casualties in GTD and construct *casualties* measuring the number of victims killed or injured by terrorist attacks. For individuals interviewed before local attacks, this variable takes the value of zero.

As reported in Table 1, the resulting casualties of the attacks in our sample are limited. Among the nine series of terrorist attacks, four did not result in any deaths or injuries. Except for the two series of attacks in Mali (December 2008) and Kenya (November 2011) which resulted in 29 and 27 casualties (14 and 4 deaths among them), respectively, all the other attacks brought less than 10 casualties (or less than 4 deaths). Therefore, unlike large-scale terrorist attacks, such as 9/11, which have been found to have a wide range of detrimental effects, we are actually focusing on attacks with low casualties.

The pessimism of individuals, as the key outcome variable, is constructed based on the question from Afrobarometer, "looking ahead, do you expect the following to be better or worse: your living conditions in twelve months time?" The answers to this question are categorized into "much better," "better," "same," "worse," and "much worse." We construct a binary variable, *worse living conditions future vs. now*, which equals one if an individual answered "worse" or "much worse" to this question, and zero otherwise. It reveals the respondents' pessimistic views of their future living conditions. Alternatively, we also construct a categorical variable, assigning the values of 1–5 to the answers from "much better" to "much worse," respectively. As reported in Table A1, 29% of respondents held pessimistic views on their own living conditions in 12 months.

Besides the main outcome variable on pessimism, we also create two auxiliary outcome variables to provide deeper insight into the impact of terrorism. First, based on the question "looking back, how do you rate the following compared to twelve months ago: your living conditions?" we construct another binary variable, *worse living conditions now vs. past*, which equals one for those whose answers were "worse" or "much worse," and zero otherwise. It measures one's evaluation of the current living conditions compared with the past. We employ it to investigate whether the attacks in the local region had direct consequences on residents' living conditions.

The second auxiliary outcome captures individuals' expectations of the national economy. Besides being asked about their own living conditions, the respondents were also asked "looking ahead, do you expect the following to be better or worse: economic conditions in this country in twelve months time?" The binary variable, *worse national economy worse future vs. now*, is one for the individuals who expected a worse national economy in the future, and zero otherwise. We use it to distinguish between respondents' pessimistic view of their own lives from their expectations of the national economy. Table A1 shows that 42% of individuals in our sample evaluated their current living conditions as worse than 12 months ago, and 36% expected a worse national economy in 12 months.

We also obtain demographic variables from Afrobarometer, including gender, age, education, employment status, etc. The summary statistics are reported in Table A1. In our sample, half of the individuals are female. The respondents' age is from 18 to 86, with an average of 34. About 39% of the respondents have received primary education, 33% secondary education, and 16% post-secondary education. At the time of survey, 60% of respondents were unemployed. About 67% of the respondents resided in rural areas. The average distance from the local attack to the respondents' enumeration area is 124 km.

2.3. Main regression specification

Our identification strategy relies on the randomness between the timing of terrorist attacks and the timing of the fieldwork of Afrobarometer surveys. It creates a plausibly exogenous variation in respondents' exposure to the terrorist attacks in the local region. We estimate the impact of terrorist attacks on the respondents' pessimistic views based on the following specification:

$$y_{ipt} = \beta attack_i + \delta X_i + \lambda_{pt} + \varepsilon_{ipt} \tag{1}$$

where y_{ipt} denotes the outcome variables for individual i from region p, interviewed in wave t. It refers to the binary variable, *worse living conditions future vs. now*, for the benchmark analyses. The main independent

[7] In Table 6, we show that the results are robust if we only focus on the six regions with single attack.

Table 1
Attacks and interviews in matched regions.

First attack date	# of attacks	# of deaths	# of injuries	Country	Region	# of days relative to attacks		# of people interviewed relative to attacks			# of interviewers
						Before	After	Before	After	Total	
2008.05.18	3	2	0	Nigeria	Rivers	2	7	32	120	152	4
2008.08.15	2	2	7	Uganda	North	19	4	416	119	535	16
2008.08.18	1	0	0	Uganda	Central	5	71	144	384	528	22
2008.11.09	1	0	0	Kenya	North Eastern	10	2	64	32	96	6
2008.12.21	1	14	15	Mali	Bamako	5	5	80	48	128	3
2011.11.23	6	4	23	Kenya	North Eastern	7	13	40	72	112	8
2012.11.01	1	4	1	Nigeria	Plateau	1	1	16	32	48	4
2012.11.07	1	0	0	Nigeria	Borno	5	71	36	28	64	4
2013.01.12	1	0	0	Tunisia	Tunis	2	16	39	81	120	13

Note: This table presents summarized information on the nine matched region-wave cells, including the date of the attack (or the first attack in the three cells with multiple attacks), number of attacks and resulting casualties in each cell, length of time covered by Afrobarometer surveys before and after the attack, number of respondents interviewed before and after the attack, and number of interviewers conducting surveys.

variable of interest, $attack_i$, measures individual i's exposure to the terrorist attacks in the local region. In the baseline regressions, it refers to the dummy variable, *post*, which equals one if individual i was interviewed on or after the terrorist attacks that occurred in the same region. It is later replaced by *intensity* and *casualties*, which capture the number and resulting casualties of the local attacks, respectively. X_i is a vector of covariates including individual i's gender, age, age squared, dummies for different levels of education (i.e., no formal education, primary, secondary, or post-secondary education), dummies for different employment status (i.e., unemployed and not looking for a job, unemployed and looking for a job, part-time job, or full-time job), and a dummy variable for rural residents.

The region-wave fixed effect, λ_{pt}, allows us to identify the impact of terrorist attacks by comparing the respondents interviewed before the attacks happened in the local region with those in the same region but who were interviewed a few days later, after the attack. Since we focus on the sample in which attacks and surveys overlapped in terms of timing and region, adding this region-wave fixed effect is equivalent to including the fixed effect specific to each attack (or series of attacks, in the three cases of consecutive attacks). In other words, it ensures that we are comparing individuals who were interviewed before and after the same attack.

We further include the fixed effect specific to each interviewer. There are a total of 80 interviewers in our sample of nine region-wave cells, as reported in Table 1, each conducting interviews in the field across many primary sampling units in one country, according to the design of Afrobarometer. By including the interviewer fixed effects, we further confine our comparison to households interviewed by the same interviewer, between those interviewed before and after the local attack. This also eliminates the potential social desirability bias originating from the interviewers (Depetris-Chauvin et al., 2020).[8]

Standard errors are clustered at different levels for inferences. In the benchmark specification, we cluster the standard errors at the interviewer level, allowing for the correlation of respondents accessed by the same interviewer. To be more conservative, we also cluster at the region-wave level (same as the attack level). Since there are only nine region-wave cells, we also adopt the wild cluster bootstrap method as in Cameron et al. (2008), with 1000 times of resampling.

Our identification strategy relies on the plausibly exogenous timing of terrorist attacks relative to the timing of Afrobarometer surveys. Since it uses scenarios where the timeline of survey in one region overlapped with the date of attack in the same region, it provides a unique advantage in understanding individuals' immediate responses to the local attacks, as the Afrobarometer survey within one region typically lasted less than a month. We probe more into this short-run impact on terrorist attacks by narrowing the time window, focusing on the sample of respondents interviewed within 15 days around the local attack (90% of observations) and further on respondents interviewed within 3 days immediately before and after the attack (41% of observations). But the other side of the coin is that, given the limited time window of fieldwork in one region, a reliable estimation of the persistent effects caused by local terrorist attacks is beyond the scope of this empirical setting.

2.4. Threats to identification

The assumption underlying our identification strategy is that the fieldwork of Afrobarometer surveys should not interfere with the terrorist attacks in that region. While it is unimaginable that terrorist organizations and Afrobarometer would coordinate their activities, it is possible that the implementation of the survey might be different in the presence of terrorist attacks in the region. As a result, the respondents accessed after the attacks may be systematically different from those who were interviewed within a few days before the attack. We try to address this concern from a number of different perspectives.

First, the Afrobarometer team employs random selection methods at every stage of sampling.[9] The sampling units had been randomly selected before the fieldwork started, and hence, before the attacks occurred in the local region. At the interview stage, the interviewers randomly selected their starting points in each primary sampling area (which was also before the attacks) and then followed a random walk pattern to choose households (and members) for interviews. The selected individuals are then back-checked by the field supervisors to ensure randomness and representativeness.[10] Therefore, it is unlikely that the low-casualty attacks in our sample which occurred during the survey stage would affect the overall random sampling design at the earlier stage, or the implementation of surveys in the entire region. This is confirmed by the robustness of the main results when we exclude the areas close to the attacks or when we focus only on attacks without casualties in Section 3.4. In both cases, the attacks were especially unlikely to affect the fieldwork of the survey, due to their remoteness and

[8] Including the interviewer fixed effects produces the same results as interacting the region-wave fixed effects with interviewer fixed effects, since we do not have the same interviewers spanning multiple region-wave cells in our sample. The variation we use comes from the different exposure to attacks of respondents with the same interviewer in the same region and survey wave.

[9] See http://afrobarometer.org/surveys-and-methods/sampling-principles.

[10] The starting points are chosen by first drawing grids on area maps and then randomly picking coordinates on the gridded maps. Households are then selected by using the walk pattern of 5/10 interval. In our sample, an interviewer typically covers eight or four households in one enumeration, depending on the country's sampling size (2400 or 1200). For more details, see Afrobarometer survey manuals accessed from https://afrobarometer.org/surveys-and-methods.

Table 2
Balance tests.

	Pre-attack	Post-attack	Coefficient	P-value
	(1)	(2)	(3)	(4)
Panel A: within ± 15 days				
Female	0.50	0.50	−0.003	0.578
Age	33.67	34.78	1.139	0.166
Education: No formal	0.15	0.11	−0.012	0.615
Primary	0.42	0.37	−0.020	0.448
Secondary	0.29	0.35	0.015	0.572
Post-secondary	0.14	0.17	0.017	0.424
Unemployed	0.62	0.57	0.000	0.989
Rural	0.58	0.72	0.149	0.001
Distance	148.5	95.34	−10.81	0.149
Number of attempts	1.03	1.05	0.008	0.520
Trust others	1.64	1.49	0.032	0.655
Cooperative	0.82	0.76	−0.023	0.430
Uncooperative	0.01	0.01	−0.004	0.614
Panel B: within ± 3 days				
Female	0.50	0.50	−0.004	0.615
Age	33.81	34.45	1.118	0.247
Education: No formal	0.13	0.13	0.017	0.573
Primary	0.39	0.32	−0.043	0.265
Secondary	0.31	0.34	−0.010	0.778
Post-secondary	0.16	0.22	0.036	0.210
Unemployed	0.58	0.58	0.010	0.804
Rural	0.45	0.62	0.164	0.003
Distance	92.90	123.3	25.46	0.001
Number of attempts	1.05	1.07	−0.000	0.988
Trust others	1.49	1.51	0.080	0.261
Cooperative	0.83	0.77	−0.042	0.224
Uncooperative	0.01	0.01	0.004	0.635

Note: This table presents the balance tests comparing pre- and post-attack respondents. The coefficients in column 3 are obtained from the regressions of each variable on the treatment dummy, *post*, while controlling for the region-wave fixed effects and clustering the standard errors at the interviewer level. The p-values associated with these coefficients are reported in column 4.

limited physical consequences.

Second, we examine the validity of our identification strategy by conducting balance tests comparing the respondents interviewed before and after the attacks across their observed characteristics, including gender, age, education level, employment status, residing area, and distance from the attacks. In columns 1 and 2 of Table 2, we report the means of these covariables for the respondents interviewed before attacks and for the post-attack respondents, respectively. To make sure that we are comparing individuals interviewed in the same region-wave cell (i.e., before and after the same attack), we regress each of these variables on the treatment dummy, *post*, controlling for the region-wave fixed effects and clustering the standard errors at the interviewer level. The coefficients and p-values are reported in columns 3 and 4, respectively.

The individual characteristics are largely balanced when we compare the respondents interviewed within 15 days before and after the attack in panel A and those surveyed within 3 days in panel B. The only exceptions are *rural* and *distance* (in panel B). The respondents interviewed within three days after an attack were more distant from the attack than those interviewed within three days before the attack. But for the respondents surveyed within 15 days, the distance from attack is not significantly different between the pre- and post-attack respondents, and the coefficient is in an opposite sign. Regarding rural status, individuals interviewed after the attacks were more likely to be rural residents. Since the attacks tend to target urban areas, these suggest a possibility that individuals near an attack are less likely to respond after the attack occurs.[11] However, if these people held more negative attitudes in general and were less likely to accept the survey, they were also more likely to be pessimistic. Hence, their absence from the sample would lead to an underestimation of the attack's impact on people's pessimistic views. In any event, we control for these individual characteristics in the regression analyses and particularly examine the impact across rural status and distance from the local attacks.

Lastly, we investigate this possibility directly by looking at interviewers' attempts to reach respondents and respondents' attitudes during the survey. First, Afrobarometer data contain interviewers' reported number of calls made to households. It reflects households' responsiveness directly. We also collect respondents' self-reported trust toward others and the interviewers' evaluation of the respondents' cooperativeness.[12] As reported in both panels of Table 2, the post-attack respondents do not differ from the pre-attack ones in terms of trust toward others, (un)cooperativeness, or responsiveness.

3. The impact of terrorist attacks on pessimism

3.1. Graphical evidence

We start with a graphical presentation of our main results on the impact of exposure to terrorism on pessimism. In panel A of Fig. 2, we plot respondents' average beliefs about their future living conditions, net of region-wave fixed effects, as a function of the (standardized) date on which they are interviewed relative to the attack in the local region. Panel B plots a different version of the results in which we include all the terms specified in Eq. (1), including individuals' gender, age, age squared, educational attainment, employment and rural-urban status, and the region-wave and interviewer fixed effects. Panel C focuses on attacks with zero casualties, taking into account both deaths and injuries. In all panels, the standardized date on the x-axis denotes the number of days between the date of terrorist events and the date when respondents are interviewed. The size of the circle indicates the relative number of respondents surveyed on each standardized date. We fit the points using both a number-of-observations weighted linear function and a kernel-weighted local polynomial function before and after the terrorist events.[13]

As clearly shown in all three panels of Fig. 2, those with exposure to terrorist attacks prior to interviews are more likely to express negative views of their future living conditions than those without the exposure. There are clear jumps at the date when local attacks occurred. The jump is larger around the zero-casualty attacks in panel C. Taken together, these figures suggest that low-casualty terrorist attacks significantly increase pessimism among exposed people.[14]

3.2. Baseline results

We next examine the impact of exposure to terrorism on pessimism by estimating Eq. (1). Our outcome variable is *worse living conditions future vs. now*, which equals one if the respondents expect their living conditions in 12 months to be worse or much worse than now, and zero otherwise. In Table 3, we report the coefficients of the key independent

[11] We are grateful to one anonymous referee for this point.

[12] The variable of trust toward others takes a value from zero to three, representing "not at all," "just a little," "I trust them somewhat," and "I trust them a lot," respectively. For (un)cooperativeness, interviewers were asked whether the respondent's attitude toward the interviewer was "cooperative," "in between," or "uncooperative" during the interview. The variable on cooperativeness equals one if the answer was "cooperative," while the variable on uncooperativeness equals one if the answer was "uncooperative."

[13] In the kernel-weighted local polynomial function, we adopt a bandwidth of 5 days, epanechnikov kernel function, and a zero degree of polynomial smooth by default.

[14] In Appendix Fig. A2, we plot people's evaluations on current living conditions compared to the past around the attacks. The fitted lines and curves are smooth around the attacks, without discontinuities. This suggests that the results are not driven by the potential direct damages caused by the terror events, consistent with the findings in Table 4.

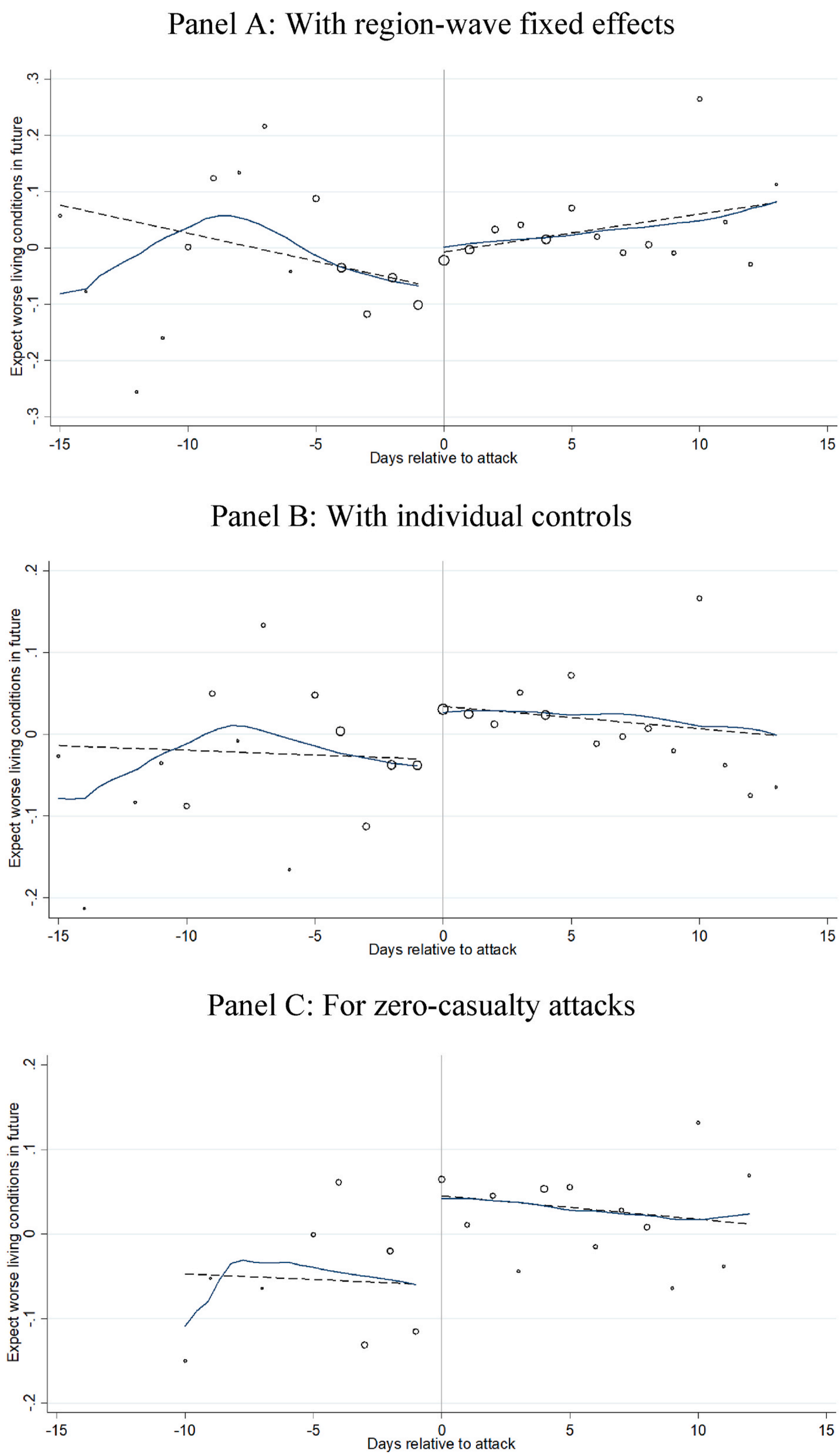

Fig. 2. Beliefs about Future Living Conditions around Terrorist Attacks. *Note*: This figure plots respondents' average beliefs about their future living conditions across the days relative to terrorist attacks. The y-axis in panel A is the residual of regressing *worse living conditions future vs. now* on the region-wave fixed effect, while the y-axis in panels B and C is the residual after we add individual characteristics as covariates, including age, age squared, gender, educational attainment, employment status, living areas, and the interviewer dummies. Panel C only focuses on attacks with zero casualties. In all panels, the x-axis denotes the days between the interviews and terrorist attacks in the same region. Zero indicates the day of terrorist attacks. The size of the circle represents the number of people interviewed on each day. We fit the points both linearly, weighted by the number of observations, and using a kernel-weighted local polynomial function on each side of the attacks.

Table 3
Impact of terrorist attacks on pessimism.

Mean of Y before attack	Dependent variable: worse living condition future vs. now			
	0.26	0.26	0.17	0.16
	(1)	(2)	(3)	(4)
Post	0.06	0.08	0.09	0.11
SE interviewer	(0.04)	(0.03)***	(0.04)**	(0.04)***
SE region-wave	[0.06]	[0.03]**	[0.04]**	[0.03]**
Bootstrap p-value	{0.35}	{0.00}***	{0.04}**	{0.00}***
Individual covariates		Yes		Yes
Interviewer FE		Yes		Yes
Region-wave FE	Yes	Yes	Yes	Yes
Sample	±15 days	±15 days	±3 days	±3 days
Observations	1410	1394	654	644
R-squared	0.09	0.35	0.16	0.33

Note: This table estimates the effects of exposure to terrorist attacks on people's pessimistic views. The dependent variable is *worse living condition future vs. now*, which is a dummy variable equal to 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. In columns 1 and 3, we only include the region-wave fixed effects. In columns 2 and 4, we further add the interviewer fixed effect and individual covariates specified in Eq. (1), including respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. The first two columns use the sample that contains respondents interviewed within 15 days before and after the attacks, while columns 3 and 4 focus on respondents interviewed within 3 days before and after the attacks. Standard errors clustered at the interviewer level are reported in parentheses. Standard errors are clustered at the region-wave level in the square brackets, and p-values from wild cluster bootstrap with 1000 repetitions are in curly brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

variable, *post*, which equals one if respondents are interviewed on or after the date of the (first) terrorist attack in the region, and zero otherwise.[15] In columns 1 and 3, we only include the region-wave fixed effects. In columns 2 and 4, we further add respondents' characteristics and the interviewer fixed effect specified in Eq. (1). The first two columns use the sample that contains respondents interviewed within 15 days before and after the attacks, while columns 3 and 4 focus on respondents interviewed within 3 days before and after the attacks.

Across all columns, our coefficients on *post* are positive and large compared to the pre-attack means. In our preferred specification with the complete set of controls and fixed effects (columns 2 and 4), the coefficients on *post* are stable, positive, and statistically significant at least at the 95% confidence level. This indicates that exposure to terrorist attacks increases the probability of respondents expressing pessimistic views on future living conditions significantly. The size of the coefficients is economically large. Comparing the individuals interviewed within 15 days before and after the attack in the local region in column 2, we find terrorism makes people 8 percentage points more likely to express pessimistic views of their future living conditions, a 31% jump relative to the pre-attack sample average. When we focus on individuals interviewed within 3 days immediately before and after the attacks in column 4, people with exposure to terrorist attacks are 11 percentage points more likely to express negative views on their future living conditions, a 69% jump compared to the pre-attack average. Consistent with the evidence in Fig. 2, this reveals a clear discontinuity in people's pessimistic views at the time of the local attack. We interpret this as evidence that terrorist attacks affect people's psychological well-being.

[15] Following the convention in the literature (e.g., Balcells and Torrats-Espinosa, 2018), we assume that respondents in our sample are aware of the terrorist attacks in their province/state the same day or the day after the attacks took place. The GTA database also reports information on the date when the attacks are reported by popular media in the region. Nearly all of the media reports are on the same day as the attack, or the day after.

We cluster the standard errors at different levels. In the benchmark specification, we cluster the standard errors at the interviewer level, allowing for correlation among the respondents surveyed by the same interviewer.[16] The standard errors are reported in parentheses in Table 3. To be more conservative, we also cluster at the region-wave level (same as the attack level) and report the standard errors in the brackets. Since there are only nine region-wave clusters, we further adopt the wild cluster bootstrap method and report the p-values in the curly brackets. The results become statistically stronger.

3.3. Alternative interpretations

An immediate concern following the main finding is that the change in beliefs about living conditions in 12 months may be driven by the direct damages caused by terrorist attacks. Even though the attacks in our sample are mostly low-casualty ones and happen, on average, 124 km away from respondents' enumeration areas, it is still possible that the pessimistic views are driven by respondents for whom terror attacks imposed direct damages, rather than through the psychological channel.

To test the relevance of this alternative interpretation, we re-estimate Eq. (1), with *worse living condition now vs. past* as the dependent variable. It equals one if respondents think their current living conditions are worse or much worse than 12 months ago, and zero otherwise. By comparing the value of this variable between people interviewed immediately before and after terrorist attacks, we can gauge the direct damages of terrorist events on people's living conditions. As reported in panel A of Table 4, we find that none of the coefficients on *post* are statistically meaningful. Therefore, our main finding is unlikely to be completely driven by the direct damages caused by terrorist attacks.

A related concern is that the respondents' pessimistic views on living conditions may be driven by their beliefs about the prospects of the national economy. Although this possibility also reflects the psychological impact of terrorist attacks on exposed people, it is a different mechanism than our interpretation. While we stress the direct impact of terrorism on people's mental attitude, this alternative interpretation suggests a spillover effect from respondents' pessimistic view on the national economy after attacks to their pessimistic views on their future living conditions. We evaluate the empirical relevance of this alternative interpretation by re-estimating Eq. (1) using *worse national economy future vs. now* as the dependent variable. Panel B of Table 4 tabulates the regression results. Again, though the coefficients on *post* are positive, which implies that terror attacks worsen people's beliefs about the prospects of the national economy, the effects are relatively small and statistically insignificant, except for one case in column 3 where we only include the region-wave fixed effects and cluster the standard errors at the interviewer level. Overall, it indicates that our main result is unlikely to solely reflect the change in people's views on the national economy in the future.

3.4. Robustness checks

We explore the robustness of the results from a number of different perspectives. We start by considering two alternative measures of attack exposure, i.e., *intensity* and *casualties*. Table 5 presents the results. In columns 1, 3, 5, and 7, we only include the region-wave fixed effect in the regressions. In columns 2, 4, 6, and 8, we further include individual covariates and the interviewer fixed effect. We employ the sample of respondents interviewed within 15 days before and after the attacks in columns 1, 2, 5, and 6, while in columns 3, 4, 7, and 8, we focus on the respondents interviewed within 3 days around the attacks. As reported in Table 5, the coefficients on *intensity* and *casualties*, across all

[16] There are 73 and 64 interviewers, respectively, in the samples used in columns 2 and 4.

Table 4
Impact of terrorist attacks on other beliefs.

Panel A	Dependent variable: worse living conditions now vs. past			
Mean of Y before attack	0.41	0.41	0.37	0.37
	(1)	(2)	(3)	(4)
Post	0.03	0.05	−0.003	0.03
SE interviewer	(0.04)	(0.03)	(0.04)	(0.04)
SE region-wave	[0.05]	[0.03]	[0.06]	[0.03]
Bootstrap p-value	{0.53}	{0.26}	{0.95}	{0.53}
Individual covariates		Yes		Yes
Interviewer FE		Yes		Yes
Region-wave FE	Yes	Yes	Yes	Yes
Sample	±15 days	±15 days	±3 days	±3 days
Observations	1579	1560	728	716
R-squared	0.08	0.25	0.10	0.26
Panel B	Dependent variable: worse national economy future vs. now			
Mean of Y before attack	0.32	0.32	0.25	0.24
	(1)	(2)	(3)	(4)
Post	0.03	0.03	0.06	0.05
SE interviewer	(0.04)	(0.03)	(0.04)*	(0.04)
SE region-wave	[0.05]	[0.03]	[0.04]	[0.04]
Bootstrap p-value	{0.71}	{0.24}	{0.21}	{0.25}
Individual covariates		Yes		Yes
Interviewer FE		Yes		Yes
Region-wave FE	Yes	Yes	Yes	Yes
Sample	±15 days	±15 days	±3 days	±3 days
Observations	1412	1394	654	642
R-squared	0.07	0.30	0.11	0.32

Note: In panel A, the dependent variable is *worse living condition now vs. past*, which is a dummy variable that equals 1 if respondents think their current living conditions are worse or much worse than 12 months ago, and 0 otherwise. In panel B, the dependent variable is *worse national economy now vs. past*, which is a dummy variable that equals 1 if respondents think the national economy will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. In columns 1 and 3, we only include the region-wave fixed effects. In columns 2 and 4, we further add the interviewer fixed effect and individual covariates specified in Eq. (1), including respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. The first two columns use the sample that contains respondents interviewed within 15 days before and after the attacks, while columns 3 and 4 focus on respondents interviewed within 3 days before and after the attacks. Standard errors clustered at the interviewer level are reported in parentheses. Standard errors are clustered at the region-wave level in square brackets, and p-values from wild cluster bootstrap with 1000 repetitions are in curly brackets. ***p < 0.01, **p < 0.05, *p < 0.1.

specifications, are statistically significant at least at the 95% confidence levels. For the economic magnitude, for example, the estimate from column 4 indicates that an additional terror attack increases the probability of holding pessimistic views by 9 percentage points, close to the effects we obtained in the baseline analyses in Table 3.

Regarding the resulting deaths and injuries from terror attacks, the coefficient in column 8 implies that for each victim killed or injured in the terrorist attacks, respondents exposed to the attacks are 0.3 percentage points more likely to express pessimistic views on their future living conditions. This impact of casualty is relatively small given that the pre-attack average of *worse living conditions future vs. now* is 16%. This is consistent with our conjecture that the impact of these low-casualty terror acts on pessimism is mostly due to the occurrence of attacks. It is relatively less sensitive to the number of casualties.

To further test our conjecture that even low-casualty attacks have substantial effects on pessimism, we restrict our sample to respondents interviewed around the four attacks which resulted in zero deaths or injuries. We present the results in column 1 of Table 6. Those interviewed within 15 and 3 days around the attacks are employed respectively, in panels A and B. The estimates of the impact on pessimism become larger than those in the baseline regressions in Table 3.

Next, the effect might be amplified by the three region-wave cells where multiple attacks occurred within a few days. To address this concern, we exclude these cases in column 2 of Table 6. In column 3, we add more covariates measuring respondents' religion and ethnicity. It is likely that individuals from advantaged groups (e.g., from a certain religion or the ethnic majority) in a country may hold different views toward future living conditions. In column 4, we construct our working sample in a different way. Instead of relying on administrative boundaries to obtain the regions where Afrobarometer surveys overlapped with terrorist attacks, we now obtain the sample of respondents based on geographical distance, i.e., whether the respondents live within a radius of 200 km from the attacks. In all these columns, the results are almost the same as the baseline analyses.

We also employ a Probit model since the dependent variable is binary. The marginal effects are reported in column 5. In this non-linear model, the magnitudes of the effects are slightly larger than the baseline OLS results. In column 6, we use the ordinal measure of pessimism as the dependent variable. The results are qualitatively the same. Again, the impact of terrorism is larger when we focus on respondents interviewed within three days before and after the attacks. In column 7, we restrict our sample to respondents who live further than 116 km from the attacks (the median), but still within the same region; the effects are slightly larger than the baseline. It confirms that the effect on the pessimistic view toward future living conditions is unlikely to be driven by direct damages of the attacks. It also alleviates the concern that the impact of terrorism may by induced by the potential selection of respondents who are directly affected by the attacks.

We also conduct a number of sensitivity and falsification tests. For example, to investigate whether the results are sensitive to the choice of time windows around local attacks, we focus on different samples based on different lengths of time window, ranging from 3 to 15 days, before and after the attacks. We re-estimate Eq. (1) using these samples and plot the coefficients with the 95% confidence intervals in Fig. 3. The estimates of the terrorism impact are very stable across different time windows. Although the empirical design of this paper does not allow for a reliable estimation of the long-term effects, we find the effects of terrorism on pessimism are persistent at least within the span of 15 days before and after the attacks. In Appendix Fig. A3, we drop one of the nine terrorist attacks each time from our sample and plot the estimates. This shows that our results are not driven by any particular terrorist event. In Appendix Fig. A4, we explore whether our results may capture the effects of other concurrent incidents that are potentially correlated with people's pessimistic views. We randomly assign the dates of attacks within the event-overlapped survey windows in each affected region and re-estimate Eq. (1) with our full set of covariates and fixed effects 1000 times. The distribution of the placebo coefficients centers around zero, whereas the baseline estimate (0.11) lies outside the 99% confidence interval of the distribution (0.09). This suggests that our results are unlikely to be a simple reflection of other concurrent shocks.

3.5. Heterogeneous analyses

We conduct a number of heterogeneity tests to further understand the relationship between exposure to terrorist attacks and people's pessimistic views. Based on the information on the targets and victims of the terrorist attacks, we group the attacks into three types: attacks on civilians (68%), attacks on public sectors (20%), and attacks on religious figures (12%).[17] We add to Eq. (1) the interaction term of *post*, with the dummy variable indicating each type of attack, and report the results in

[17] The dummy variable *civilian* equals one if the targets of the attacks are private citizens and property, business, or transportation. The variable *public* equals one if the targets are government, police, or military. The variable *religious* equals one if the targets are religious figures or institutions.

Table 5
Alternative measures of terrorism exposure and pessimism.

Dependent variable: worse living condition future vs. now								
Mean of Y before attack	0.26	0.26	0.17	0.16	0.26	0.26	0.17	0.16
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intensity	0.038***	0.033**	0.071**	0.091***				
	(0.014)	(0.016)	(0.034)	(0.031)				
Casualties					0.005**	0.003***	0.003**	0.003**
					(0.002)	(0.001)	(0.002)	(0.001)
Individual covariates		Yes		Yes		Yes		Yes
Interviewer FE		Yes		Yes		Yes		Yes
Region-wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	15 days	15 days	3 days	3 days	15 days	15 days	3 days	3 days
Observations	1410	1394	654	644	1410	1394	654	644
R-squared	0.096	0.345	0.157	0.327	0.093	0.344	0.149	0.316

Note: The dependent variable is *worse living condition future vs. now*, which is a dummy variable that equals 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dependent variable *intensity* equals the number of attacks in the local region at the time of the interview. It is zero if the individuals were interviewed before the local attacks happened. The variable *casualties* measures the number of victims killed or injured by terrorist attacks. For the individuals interviewed before local attacks, this variable takes the value of zero. In odd columns, we only include the region-wave fixed effects. In even columns, we further add the interviewer fixed effect and individual covariates specified in Eq. (1), including respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. Columns 1, 2, 5, and 6 use the sample that contains respondents interviewed within 15 days before and after the attacks, while columns 3, 4, 7, and 8 focus on respondents interviewed within 3 days before and after the attacks. Standard errors clustered at the interviewer level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6
Robustness checks.

	No casualties	Single attacks	More individual covariates	200 km	Probit	Ordinal pessimism	Distance > median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: within ± 15 days							
Post	0.12**	0.09***	0.08**	0.08***	0.10***	0.22**	0.13***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.10)	(0.04)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	674	1207	1290	1222	1185	1290	665
R-squared	0.26	0.36	0.37	0.33	0.25	0.45	0.42
Panel B: within ± 3 days							
Post	0.16***	0.11***	0.11***	0.09**	0.14***	0.26**	0.21***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)	(0.06)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	314	602	561	566	491	561	288
R-squared	0.30	0.35	0.36	0.33	0.24	0.45	0.41

Note: This table presents the results from robustness checks. The dependent variable is *worse living condition future vs. now*, which is a dummy variable that equals 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. Individual covariates include respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. Panel A uses the sample that contains respondents interviewed within 15 days before and after the attacks, while panel B focuses on respondents interviewed within 3 days before and after the attacks. Column 1 focuses on four terror attacks without deaths or injuries. Column 2 looks at six region-wave cells with single attacks. The individual covariates, including a dummy for ethnic majority and religion dummies, are added in column 3. Column 4 contains the sample of respondents living within a radius of 200 km from the attacks. The marginal effects from a Probit model are reported in column 5. Column 6 uses the ordinal measure of pessimism as the dependent variable. Column 7 only includes respondents whose distance from the attacks in the same region is above the median. Standard errors clustered at the interviewer level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 7. We find that while attacks on civilians or the public sector do not generate significantly different effects, the impact of terrorism on people's pessimistic views is stronger when attacks are directed against religious leaders or institutions. The results are consistent in panels A and B, where we focus on the windows of 15 and 3 days, respectively. This may not be surprising given the important role religion plays in Africa. In our sample, specifically, all the respondents report that they have some religion, and 85% of them view religion as "very important."[18]

We also categorize the attacks into different groups based on the type of attack, such as armed assault, bombing or explosion, and kidnapping, and we include the interaction terms in the regressions. The results in columns 4–6 of Table 7 suggest that the impact of terrorism is not significantly different across these different types of attacks.

We also investigate the effect separately for respondents living in rural and urban areas. Appendix Table A3 shows that while terrorist

[18] In Appendix Table A2, we find that the impact of attacks on religious figures further increases by 40–50% if we focus on the subsample of respondents who view religion as "very important" in their lives.

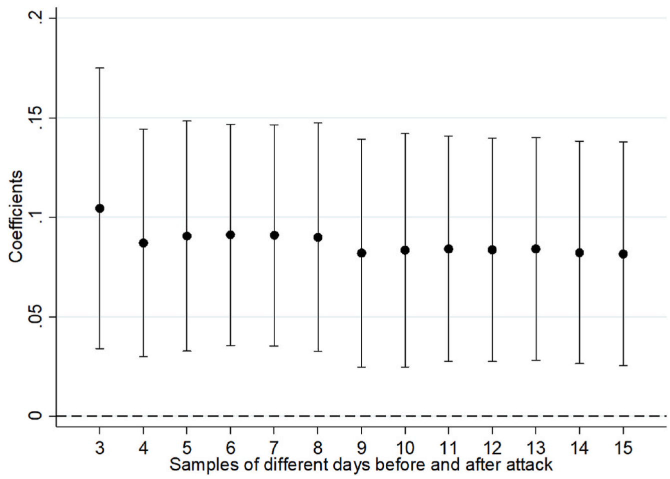

Fig. 3. Impact on Pessimism across Different Time Windows. *Note*: This figure plots the coefficients and the 95% confidence intervals of *post* from different samples in which we restrict to the respondents interviewed within different time window lengths around the attacks. The x-axis denotes the number of days around the attacks within which the respondents were interviewed.

attacks increase pessimistic views for both rural and urban residents, the effect is larger and more significant for those living in rural areas. We think this is likely due to the fact that there is a lack of public security infrastructure in rural Africa. In our sample, 77% of urban enumeration areas have police stations within walking distance, whereas only 27% of rural areas have similar security infrastructure. Hence, rural residents may feel less secure and tend to be more vulnerable to terror attacks, leading to a stronger impact of terror attacks on their pessimism.[19] This is also policy-relevant. Given that African countries generally have limited state capacity, it sheds light on where and how to maximize the limited resources to build resilience in fragile, conflict-affected areas (Blattman and Miguel, 2010; Bauer et al., 2016).

4. Discussions on the consequences of pessimism

4.1. Economic consequences

In this section, we examine how the impact of terrorist attacks on pessimism may be relevant to economic outcomes. Ideally, if there were data on individuals' economic decisions which may quickly respond to the sudden occurrence of terrorist attacks, we could include them directly as the outcome variables in our current empirical setting and (causally) study people's economic response to terror attacks. But, to the best of our knowledge, such data do not exist for our sample. Alternatively, we conduct a number of suggestive, correlational analyses here to shed some light on this issue. Before proceeding to our analysis, we stress that due to the lack of economic variables with high-frequency changes, we do not have a credible identification strategy in this section of analysis. Therefore, our findings here may be confounded by omitted variables and reverse causation. We thus caution our readers that our results here are only suggestive.

First, we collect individual-level indicators which are arguably important to individuals' socioeconomic status and local economic development. While there are no variables on individual- or household-level income in the Afrobarometer dataset, employment is an important source of income. In addition, education is a key indicator of human capital development. Therefore, we use unemployment and years of schooling as the outcome variables and regress them on the pessimism variable (in ordinal scale) in Table 8. We focus on a more comprehensive sample covering all the survey respondents of Afrobarometer (rounds 4 and 5) in the five countries in our sample. In the different columns, we gradually control for individual characteristics and include the fixed effect specific to each enumeration area (EA). The results show that individuals' pessimistic view on future living conditions is significantly associated with unemployment and years of schooling. Being more pessimistic is associated with a higher probability of being unemployed and fewer years of schooling. These relationships and scales are stable in different regression specifications. At the risk of over-interpreting our results, a one-ordinal-scale increase in the degree of pessimism (e.g., from "worse" to "much worse") is associated with a two percentage

Table 7
Heterogeneous effects.

	Dependent variable: worse living condition future vs. now					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: within ± 15 days						
Post	0.14***	0.09**	0.05*	0.09**	0.06**	0.11***
	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Post × Civilian	−0.09					
	(0.06)					
Post × Public		−0.02				
		(0.05)				
Post × Religious			0.20**			
			(0.09)			
Post × Armed				−0.03		
				(0.05)		
Post × Bomb					0.15	
					(0.11)	
Post × Kidnap						−0.06
						(0.06)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1394	1394	1394	1394	1394	1394
R-squared	0.35	0.35	0.35	0.35	0.35	0.35
Panel B: within ± 3 days						
Post	0.14***	0.12**	0.07*	0.13**	0.08**	0.12***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Post × Civilian	−0.07					
	(0.07)					
Post × Public		−0.04				
		(0.06)				
Post × Religious			0.16*			
			(0.09)			
Post × Armed				−0.07		
				(0.06)		
Post × Bomb					0.16	
					(0.10)	
Post × Kidnap						−0.05
						(0.08)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	644	644	644	644	644	644
R-squared	0.33	0.33	0.33	0.33	0.33	0.33

Note: This table estimates the heterogeneous effects across the targets and types of attacks. The dependent variable is *worse living condition future vs. now*, which is a dummy variable that equals 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. Individual covariates include respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. Panel A uses the sample that contains respondents interviewed within 15 days before and after the attacks, while panel B focuses on respondents interviewed within 3 days before and after the attacks. The dummy variables *civilian*, *public*, and *religious* indicate the targets of terrorist attacks, and *armed*, *bomb*, and *kidnap* indicate the type of attacks. Standard errors clustered at the interviewer level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

[19] In untabulated analyses, we find that living close to a police station does mitigate the negative impact of terror acts on respondents' pessimistic views, though the coefficients are statistically insignificant.

Table 8
The impact of pessimism on unemployment and years of schooling.

Dependent variables	Being unemployed			Years of schooling		
	(1)	(2)	(3)	(4)	(5)	(6)
Pessimism	0.02***	0.02***	0.02***	−0.10***	−0.08**	−0.07**
	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)
Ethnicity, religion			Yes			Yes
Gender, age		Yes	Yes		Yes	Yes
EA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,781	11,713	10,349	10,522	10,483	9297
R-squared	0.24	0.28	0.28	0.38	0.41	0.44

Note: This table estimates the effects of pessimism on the probability of being unemployed and years of schooling. The observations include all the respondents in the five countries in our sample covered by waves 4 and 5 of Afrobarometer surveys. In the first three columns, the dependent variable is *being unemployed*, which is a dummy variable that equals 1 if respondents are unemployed. In columns 4, 5, and 6, the dependent variable is *years of schooling*. The independent variable, *pessimism*, is in ordinal scale, with values from 1 to 5. The fixed effects specific to enumeration areas (EA) are included in columns 1 and 4. The variables of gender, age, and age squared are added in columns 2 and 5. Columns 3 and 6 further include a dummy for ethnic majority and dummies for different religions. Standard errors clustered at the interviewer level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

points increase in the probability of being unemployed and a decrease in years of schooling of about 0.1.

Second, we calculate the average night light density during 2008–2013 for each EA of the Afrobarometer survey to measure local economic development. Specifically, we focus on the pixels covered by the radii of 25 km and 50 km, respectively, from the centroid of each EA.[20] Table A4 in the Appendix shows that, conditional on country by survey wave fixed effects, the correlation coefficient between the average degree of pessimism and light density (25 km or 50 km) at the EA level is about −0.01, significant at the 99% confidence level. The unconditional correlation is even greater, with coefficients between −0.23 and −0.19.

Next, we further provide a discussion on the economic cost of terrorism-induced pessimism by doing a rather speculative, back-of-the-envelope calculation combining the elasticity between night light density and GDP growth estimated in the literature, and our reduced-form estimates between terrorism and pessimism. In particular, we employ the estimates from Henderson et al. (2012) and Chen and Nordhaus (2015). While Henderson et al. (2012) have received the most academic attention in this field, Chen and Nordhaus (2015) provide estimates that are more suitable to our context, because their underlying data come directly from Africa and take local population density into account. The rough estimates of the economic costs are provided in Table 9. In the case of Kenya in 2008, for example, if we use the elasticity (0.28–0.32) between night light density and GDP provided in Henderson et al. (2012), given that (a) Kenya's GDP in 2008 is 35.72 billion US dollars (in 2010 constant dollars), (b) our estimated effect of terror attacks on pessimism is 0.26 (in Table 6), and (c) the conditional correlation between pessimism and night light density is 0.01, the estimated cost of the terrorist attack in Kenya in 2008 would range from 26 to 30 million US dollars, as reported in column 4.[21] Alternatively, if we adopt the elasticity estimated by Chen and Nordhaus (2015) in column 5, which is between 0.30 and 0.49, the cost would be roughly 28 to 46 million US dollars. Overall, at the risk of over-extrapolation, the low-casualty terrorist attacks in our sample can roughly translate into an average cost ranging from 90 to 157 million US dollars of GDP per attack.

We also quantify the changes in pessimism using data on local infrastructures. Appendix Table A4 shows that local pessimism at the enumeration level is negatively correlated with urban residence status and the availability of many infrastructures in the enumeration, such as electricity grids, piped water, and sewage system. Although the size of the effect of terrorism on pessimism is in general twice the magnitude of our estimated correlation coefficients between pessimism and local infrastructures, we emphasize that this comparison should not be taken at face value, because these conditional correlations are likely not causal.

Table 9
Quantifying the economic cost of terror attacks induced pessimism.

Year	Country	GDP (billion USD)	Estimated loss for terrorist attacks (in million USD)	
			Henderson et al. (2012)	Chen and Nordhaus (2015)
(1)	(2)	(3)	(4)	(5)
2008	Kenya	35.72	26–30	28–46
2008	Mali	9.68	7–8	8–12
2008	Nigeria	309.77	226–258	242–395
2008	Uganda	23.54	17–20	18–30
2011	Kenya	42.44	31–35	33–54
2012	Nigeria	396.74	289–330	309–505
2013	Tunisia	46.24	34–38	36–59
Average		123.45	90–103	96–157

Note: This table provides the back-of-the-envelope calculation of the economic costs associated with terror attacks. Column 3 provides the GDP for each country in the given year (in 2010 constant dollars). Columns 4 and 5 report the estimated loss in GDP based on the estimates from Henderson et al. (2012) and Chen and Nordhaus (2015), respectively.

It is worth noting that these are only rough quantifications of the economic costs induced by terrorism in our sample. In particular, our identification of terrorism's impact is limited to the short term (i.e., the change in pessimism within 3 and 15 days after the attacks). The persistence of the impact on pessimism in the longer term remains unknown and is beyond the scope of the current study. The results should be interpreted with this caveat in mind.

4.2. Behavioral implications

In this section, we extend the discussion by investigating whether the impact of low-casualty attacks on pessimism may shift people to more or less accurate beliefs about their future living conditions, inspired by the literature on motivated beliefs (e.g., Bénabou and Tirole, 2016).

To grasp a basic understanding of the accuracy of beliefs about future living conditions in African countries, we use the feature of the repeated Afrobarometer survey in which respondents in wave T are asked their beliefs about their living conditions in the next 12 months, while in the next wave $T+1$, respondents are asked to evaluate their current living conditions compared to 12 months ago.[22] Given the limitations that the gap between waves 4 and 5 covered in our sample is more than three years, much longer than 12 months and that we do not observe the same sample of respondents across different survey waves, the analysis here

[20] Data on nighttime lights are obtained from NOAA National Centers for Environmental Information (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html).

[21] 35.72 billion × 0.28 × 0.01 × 0.26 = 26 million. 35.72 billion × 0.32 × 0.01 × 0.26 = 30 million.

[22] We are grateful to one anonymous referee for this important suggestion.

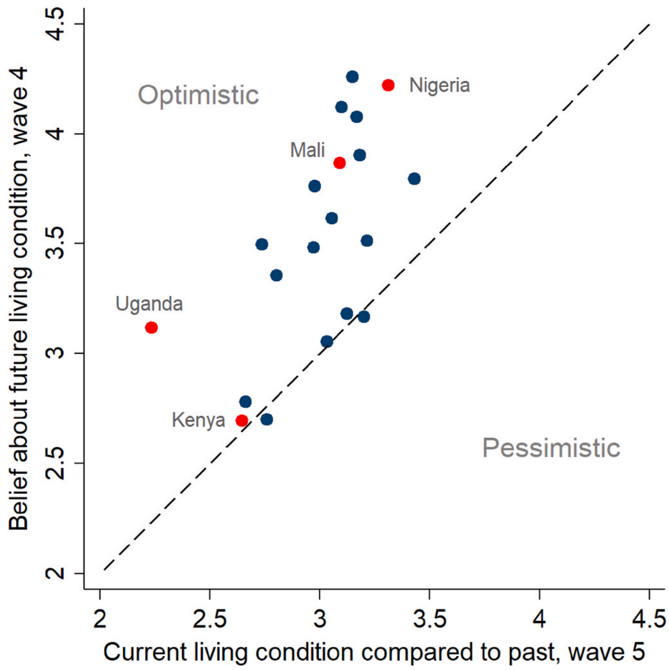

Fig. 4. Beliefs about Living Conditions across Waves. *Note*: This figure plots the country-level weighted average belief about future living conditions in wave 4 of Afrobarometer (y-axis) against the evaluation of current living conditions compared with the past in wave 5 (x-axis). Each point represents one country surveyed in both waves 4 and 5. The values of 1–5 indicate the answers from "much worse" to "much better," respectively.

only provides rough and suggestive evidence.

In Fig. 4, we plot the country-level weighted average belief of future living conditions in wave 4 of Afrobarometer against the evaluation of current living conditions compared with the past in wave 5. For the 20 countries covered by both waves 4 and 5, only 6 are located close to the 45-degree line. The other 14 countries all lie in the domain where respondents are, on average, optimistic about their future living conditions. For the countries covered in our main analysis, Nigeria, Mali, and Uganda are all above the 45-degree line; only Kenya falls on it.[23] Since terrorist attacks, on average, increase ordinal pessimism by 22 percentage points (as reported in Table 6), this suggests that the impact of terror acts on pessimism may tend to shift people toward more accurate beliefs in our sample.[24] This pattern seems to be consistent with the perspective of motivated beliefs, which stresses that most people exhibit some degree of optimism in a healthy psychological state, and it is mainly depressed individuals who seem to hold more objective beliefs (Alloy and Abrahamson, 1979; Korn et al., 2014). Our results, however, cannot say much about selective updating, a key building block of the motivated-thinking paradigm (Bénabou and Tirole, 2016). Although we discover that people exposed to terror acts do shift their views on future living conditions towards more accurate beliefs, our empirical setting does not allow us to gauge whether such changes in belief reflect the full information content of the signal (i.e., terror attacks). It is possible that the respondents in our sample process and update their beliefs to a much larger extent following the arrival of good signals, such as the victories of national football teams, as in Depetris-Chauvin et al. (2020), than bad ones, such as terrorist attacks.

5. Conclusion

This article examines the impact of exposure to low-casualty terrorist attacks on the degree of pessimism felt by people in five African countries during 2008–2013. By using a natural experiment setting, where the attacks occurred while a series of Afrobarometer surveys were being conducted, we discover that the low-casualty terror attacks in our sample lead to pessimism significantly. Compared with respondents interviewed a few days before the attacks, those who live in the same region but are interviewed immediately after the local attacks are 11% more likely to express pessimistic views of their future living conditions, a 69% jump relative to the pre-attack average, holding other factors constant. This effect is not driven by the direct damages of terrorist attacks, nor by individuals' views on the prospects of the national economy. The effects are larger when the attacks are targeted at religious figures and for respondents living in rural areas.

This paper is related to several important strands of literature. We mainly contribute to the research that examines the impact of terrorist attacks. While the majority of existing studies look at catastrophic terror events, such as 9/11, the attacks in our sample have very low casualties. We find that even these low-casualty terrorist attacks can generate substantial psychological and economic costs. Our paper also contributes to the understanding of why these low-casualty attacks have increased dramatically in Africa in the past decade. This article also adds to the literature that investigates people's post-attack psychological responses. It provides a causal approach to estimate the immediate impact of terrorism on individuals' economic beliefs by combining a large-scale representative survey with a comprehensive record of attacks.

Author statement

Jiafu An & Shiqi Guo: Conceptualization, Methodology, Software. **Shiqi Guo**: Data curation, Investigation. **Jiafu An**: Writing- Original draft preparation. **Jiafu An & Shiqi Guo**: Revision draft preparation, Reviewing and Editing.

Data availability

Data will be made available on request.

Appendix

[23] Tunisia is only covered by wave 5 of Afrobarometer survey.

[24] The mean belief of future living conditions (in ordinal scale) in wave 4 of Afrobarometer for Kenya, Mali, Nigeria, and Uganda is 3.56 (y-axis of Fig. 4), while the mean of current living condition evaluation compared with the past in wave 5 is 2.78 (x-axis of Fig. 4). Since terrorism increases the ordinal pessimism by 0.22, as reported in Table 6, after adding this treatment effect to the exante mean belief, the four countries, on average, still lie in the optimistic domain, but are closer to the 45-degree line (3.56–0.22 > 2.78). Therefore, the impact of terrorism on pessimism tends to push people to more accurate beliefs.

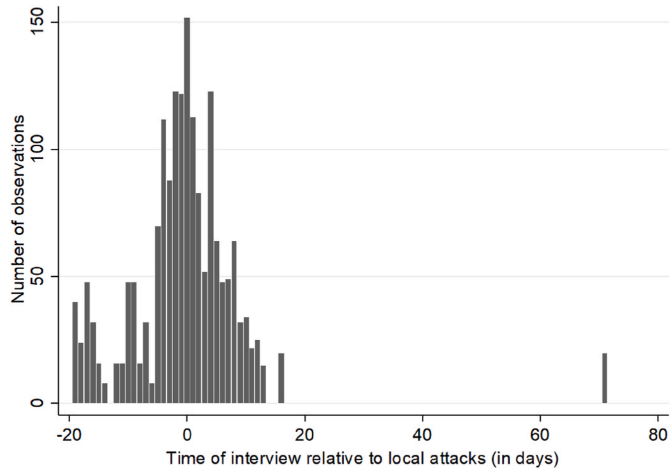

Fig. A1. Time of Interviews relative to Local Attacks. *Note*: This figure plots the number of respondents interviewed on different days relative to the attacks in the local region. About 90% of the respondents were interviewed within 15 days before and after the local attacks.

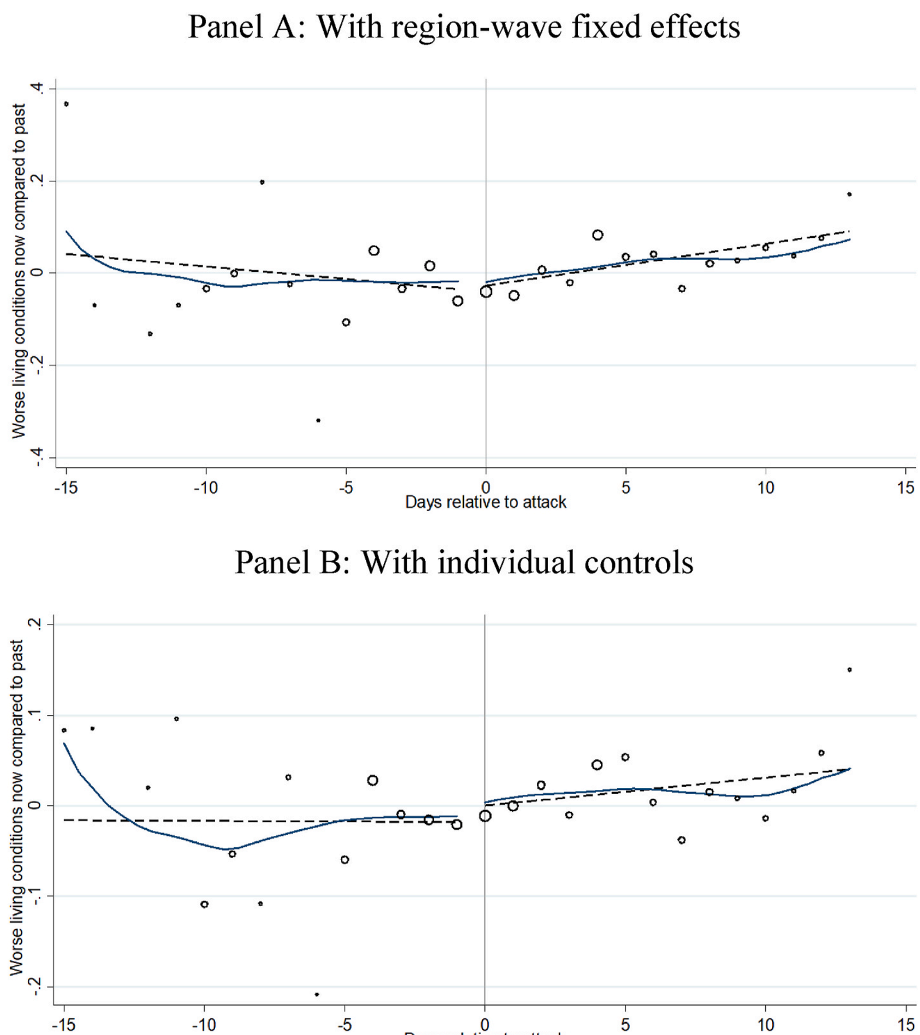

Fig. A2. Evaluations of Current Living Conditions around Terrorist Attacks. *Note*: This figure plots respondents' average evaluations of their current living conditions compared to the past across the days relative to terrorist attacks. The y-axis in panel A is the residual of regressing *worse living conditions now vs. past* on the region-wave fixed effect, while the y-axis in panel B is the residual when we add individual characteristics as covariates, including age, age squared, gender, educational attainment, employment status, living areas, and the interviewer dummies. The x-axis denotes the days between the interviews and terrorist attacks in the same region in both panels. Zero indicates the day of terrorist attacks. The size of the circle represents the number of people interviewed on each day. We fit the points both linearly, weighted by the number of observations, and using a kernel-weighted local polynomial function on each side of the attacks.

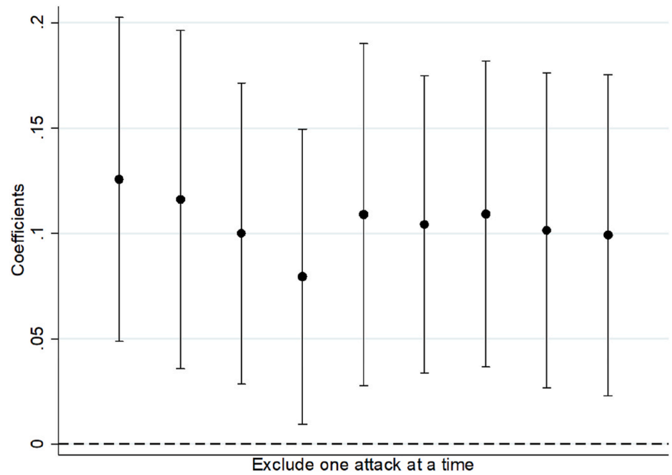

Fig. A3. Coefficients from Tests of Arbitrarily Dropping One Attack at a Time. *Note*: This figure plots the coefficients and the 95% confidence intervals of *post* from tests when we arbitrarily drop one terrorist attack at a time.

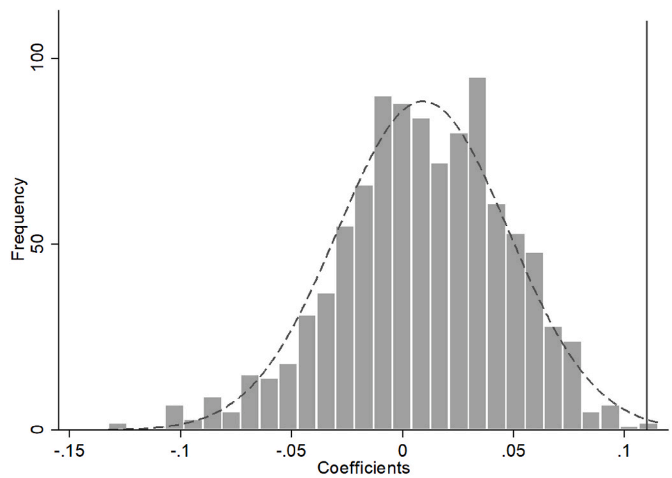

Fig. A4. Distribution of Placebo Coefficients. *Note*: This figure plots the coefficients on *post* from 1000 placebo tests where we randomly assign attack dates and therefore treatment status within our sample. The vertical line at 0.11 marks our baseline estimate from Table 3.

Table A1
Summary Statistics

Variable	Mean	SD	Min	Max	Obs.
Post	0.51	0.50	0	1	1783
Intensity	0.81	1.24	0	6	1783
Casualties	2.50	6.94	0	29	1783
Worse living conditions future vs. now	0.29	0.46	0	1	1571
Worse living conditions future vs. now (ordinal)	2.73	1.31	1	5	1571
Worse living conditions now vs. past	0.42	0.49	0	1	1762
Worse national economy future vs. now	0.36	0.48	0	1	1573
Female	0.50	0.50	0	1	1783
Age	34.39	12.97	18	86	1773
Education: no formal	0.12	0.33	0	1	1779
Education: primary	0.39	0.49	0	1	1779
Education: secondary	0.33	0.47	0	1	1779
Education: post-secondary	0.16	0.37	0	1	1779
Unemployed	0.60	0.49	0	1	1776
Rural	0.67	0.47	0	1	1783
Distance	123.82	103.90	1.21	387.84	1783

Note: This table presents the summary statistics of the key variables.

Table A2
Impact of Attacks on Religious Figures

	Dependent variable: worse living condition future vs. now	
	(1)	(2)
Post	0.06**	0.08*
	(0.03)	(0.04)
Post × Religious	0.28***	0.24***
	(0.08)	(0.08)
Individual covariates	Yes	Yes
Interviewer FE	Yes	Yes
Region-wave FE	Yes	Yes
Sample	±15 days	±3 days
Observations	1149	519
R-squared	0.36	0.35

Note: This table estimates the impact on pessimism when the targets of attacks are religious figures. The sample is restricted to respondents who view religion as very important in their lives. The dependent variable is *worse living condition future vs. now*, which is a dummy variable that equals 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. Individual covariates include respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. Column 1 uses the sample that contains respondents interviewed within 15 days before and after the attacks, while column 2 focuses on respondents interviewed within 3 days before and after the attacks. The dummy variable *religious* equals 1 if the targets of terrorist attacks are religious leaders or institutions. Standard errors clustered at the interviewer level are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A3
Exposure to Terrorist Attacks and Pessimism: Urban vs. Rural

	Dependent variable: worse living condition future vs. now			
Sub-samples	Rural	Urban	Rural	Urban
Mean of Y before attack	0.33	0.15	0.20	0.13
	(1)	(2)	(3)	(4)
Post	0.11***	0.04	0.21***	0.05
	(0.04)	(0.04)	(0.06)	(0.04)
Individual covariates	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes
Region-wave FE	Yes	Yes	Yes	Yes
Sample	±15 days	±15 days	±3 days	±3 days
Observations	933	457	354	287
R-squared	0.40	0.35	0.41	0.38

Note: This table estimates the impact of terrorist attacks on pessimism in urban and rural areas. The dependent variable is *worse living condition future vs. now*, which is a dummy variable that equals 1 if respondents think their living conditions will be worse or much worse in 12 months, and 0 otherwise. The dummy variable *post* equals 1 if respondents are interviewed on or after the date of local terrorist attacks, and 0 if interviewed before. Individual covariates include respondents' age, age squared, gender, dummies for education levels, employment status, and a rural dummy. We focus on the respondents living in rural areas in columns 1 and 3, and employ the urban sample in columns 2 and 4. Columns 1 and 2 use the sample that contains respondents interviewed within 15 days before and after the attacks, while columns 3 and 4 focus on respondents interviewed within 3 days before and after the attacks. Standard errors clustered at the interviewer level are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A4
Impact of Terrorist Attacks on Pessimism in Urban and Rural Areas

	Dependent variable: pessimism in ordinal scale					
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	−0.16***					
	(0.03)					
Electricity grids		−0.10***				
		(0.04)				
Piped water			−0.13***			
			(0.03)			
Sewage system				−0.13***		
				(0.04)		
Light 25 km					−0.01***	
					(0.00)	
Light 50 km						−0.01***
						(0.00)
Country*wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1564	1564	1553	1534	1564	1564
R-squared	0.57	0.56	0.57	0.56	0.56	0.56
Correlation coefficient	−0.20	−0.24	−0.09	−0.14	−0.19	−0.23

Note: This table reports the correlations between average pessimism (in ordinal scale) and different infrastructures and night light density within the radii of 25 and 50 km at the enumeration level. The coefficients represent the correlation coefficients conditional on the country-wave fixed effects. The unconditional correlation coefficients are reported at the bottom of the table. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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