Working Paper in Economics No. 733

Everybody's a Victim? Global Terror, Well-Being and Political Attitudes

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Department of Economics, June 2018

ISSN 1403-2473 (Print)
ISSN 1403-2465 (Online)

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Abstract

Terror has become a global issue. Terror acts perpetuated by religious, nationalist or political groups around the globe can propagate distress rapidly through different channels and possibly change political attitudes. This paper suggests the first evaluation of the impact of global terror on human welfare. We combine panel datasets for Australia, Germany, Russia, Switzerland, the UK and the US. Individual well-being information for $750,000$ individual$\times$year observations, recorded on precise dates, is matched with daily information on the $70,000$ terror events that took place worldwide during 1994-2013. High-frequency data and quasi-random terror shocks of varying intensity provide the conditions for robust inference, while external validity is guaranteed by the use of large representative samples. We find a significantly negative effect of global terror on well-being, with a money-metric cost of around $6\% - 17\%$ of national income. Among diffusion channels, stock markets and economic anticipations play a minimal role, while traditional media filter the most salient events. The effect is greatly modulated by the physical, genetic or cultural proximity to the terror regions/victims. For a subset of countries, we also show that global terror has significantly increased the intention to vote for conservative parties. Heterogeneity analyses point to the mediating effect of risk perception: individuals who exhibit stronger emotional responses to terror – possibly more exposed to potential threats – are also more likely to experience a conservative shift.

Key Words : Global Terror, Subjective Well-Being, Media, Political Attitudes.

JEL Classification : C99, D60, D72, D74, I31

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1 Introduction

Intentional and indiscriminate acts of violence have been perpetuated by individuals, groups or organizations since ancient times, as a means of creating fear to achieve political, religious or ideological aims. Traditionally, the material and human costs of religious fanaticism or political radicalism have been borne by local populations and states. However, in recent years, terror has become a global issue. Violent acts are increasingly transnational in the sense that they rely on funding and infrastructures from different countries, pursue international objectives or target groups beyond national borders. In an integrated world economy, terror events also reverberate through economic channels, chiefly through stock prices (e.g. Abadie and Gardeazabal, 2003) or commodity prices (Guidolin and La Ferrara, 2010). Moreover, new information and communication technologies mean that a local event can reach people worldwide. Researchers have commented on the symbiotic relationship between mass media and terrorism (Rohner and Frey, 2007), especially now that the audience is global and terror groups seek international exposure to exert pressure. Social media has accelerated this trend and is increasingly used as a way to propagate fear at a very broad scale. As a modern psychological warfare, the "theater of terror" tends to reach far beyond the immediate victims of terrorism (Weimann, 2005).

Against this background, a comprehensive evaluation of the global impact of terror on human welfare is required. To date, most evaluations focus on the local consequences of terror. The bulk of the literature deals with economic aspects,[1] and a few studies address the social and psychological impact of terror using self-reported measures of well-being.[2] Most of them find that the loss exceeds the purely economic consequences of terror. While these studies provide evidence on the *local* experience of terror, little is known about the global welfare implications. An exception is the study by Metcalfe et al. (2011), who estimate the impact of 9/11 on mental health in the UK. A related question pertains to the subsequent effects of fear and distress on preferences and behavior. Several studies focus on the impact of terror on voting

[1] Valiño et al. (2010) survey the evaluations of direct and indirect costs of terror. Specific studies assess the local impact of terror on growth (Blomberg et al, 2004) and fiscal revenue (Chernick and Haughwout, 2006), particularly in conjunction with the effects on investment (Fielding, 2003), firms' profits and their business prospects (Frey et al., 2007) or specific sectors like tourism (Fleischer and Buccola, 2002), transportation (Blunk et al., 2006) and insurance (Cummins et al., 2003, Brown et al., 2004). Long-term impacts on health – as measured by birth weight – are studied in Camacho (2008).

[2] Frey et al. (2009) study the impact of terror events in France and Northern Ireland. Romanov et al. (2012) explore the effect of attacks on Israelis' well-being. Clark et al. (2017) investigate the impact of the 2013 Boston marathon bombing on Americans' well-being. In psychology and medical sciences, many studies have explored the local impact of attacks like 9/11 in New York (Silver et al., 2012), the July 2005 terrorist attacks in London (Rubin et al., 2005) or March 2004 attacks in Madrid (Salguero et al., 2011). Some studies address the intangible effects felt elsewhere in the country (Silver et al, 2002, Krueger, 2007).

behavior (e.g. Berrebi and Klor, 2008, Montalvo, 2011) or support of democratic institutions (e.g. Rehman and Vanin, 2017). Again, most of them consider local implications. Among exceptions, Finseraas and Listhaug (2013) study the impact of the 2008 attacks in Mumbai on fear and public opinion in Europe. In this vein, we suggest a general assessment of how the global tension of terror may affect the well-being of Western citizens, their risk perception and political attitudes. Rather than focusing on particular events like 9/11, we rely on high-frequency variation in the intensity of world terror over a long period of time.

We make use of the Global Terrorism Database (GTD hereafter), which records all terrorist acts, defined as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious or social goal through fear, coercion or intimidation". We focus on the twenty years between 1994 and 2013, a period during which around $70,000$ terror events took place across the world. We match information on these events with individual data from six countries representing around 640 million people. For this purpose, we assemble six panel datasets from Germany, the UK, Switzerland, the Russian Federation, Australia and the US. While these panels have been extensively used individually, pooling them into a large international longitudinal dataset is unique. The total sample comprises almost $750,000$ individual$\times$year observations. They all contain information on subjective well-being (SWB hereafter), notably on life satisfaction, frequently used as a proxy for utility (Kahneman and Sugden, 2005). A subset of countries additionally contain information on political attitudes. Terror events, recorded daily in the GTD, are matched to our six-country sample using interview dates. We start with regressions of daily life satisfaction on a detailed set of controls and on several measures of terror intensity, notably the total *incidence* of terror events and the total number of subsequent *fatalities* each day. Comparing individuals observed just before and after a certain day ('between' variation) provides quasi-experimental identification of the terror effect that day. We exploit this logic over a multitude of events: inference is obtained from the fluctuation in terror intensity over the $7,305$ days of the 1994-2013 period.

The results point to a significant and depressing effect of global terror on human welfare. A battery of sensitivity checks conveys that this effect is extremely stable to modeling options (data harmonization across countries, estimation methods and specifications, timing assumptions, etc.). In particular, the estimates do not change much with the inclusion of individual fixed effects, suggesting that 'between' variation provides a robust identification of the average global terror effect. On average over the period, citizens of our sampled countries are ready to give up between 6% and 17% of their income to end world terror. Although terror is expected to exacerbate fear (Becker and Rubinstein, 2011), this is an extremely large emotional response given the microscopic chances that any of the events affect these people's lives directly. Nonetheless, this result is consistent with the literature on the formation of risk perception in the context of rare events (Sunstein, 2003). Importantly, evidence is obtained here from high-frequency data and representative samples rather than from small-scale experiments. A rich heterogeneity analysis can be performed. First, the average treatment effect can be decomposed in a discrete set of days of different terror magnitudes: it shows that the SWB response increases monotonically with terror intensity. It is very large in the top quartile, containing salient events like 9/11, but the effect is not (only) driven by such events: it is sizable and very significant for days of more moderate terror intensity.

We then exploit heterogeneity across days to establish how the perception of terror threats may vary. We first distinguish between local and foreign terror. The few local events (4.4% of all events) generate much larger effects, but the impact of foreign terror – the original focus of our study – is sizable and drives our main effect. Subsequently, we test several diffusion channels. Stock markets and the anticipation of impaired economic exchanges with terror regions seem to play a modest role. A larger mediation is found through traditional and social media in a subset of countries for which media information is available. Media coverage data shows that the main TV channels in Germany, the US and the UK cover 25% of all the global terror events. They filter terror acts that are most relevant/proximate to Western audiences and that produce larger well-being effects. Interestingly, uncovered events also have a significant (even if smaller) effect, which reflects the 'background noise' of global terror, possibly conveyed by alternative information sources including social media. Another filter is distance: using variation in terror events, we show that the signal of global terror is stronger when terror harms populations that are physically, genetically, culturally or religiously close to the interviewees. Finally, we explore individual heterogeneity: people most affected by terror are older, more risk averse or feel more exposed to potential threats (for instance, because they live in densely-populated areas or near migrants from terror countries).

These results can be interpreted as a characterization of how the perception of terror threats varies (across days or individual types). Experimental evidence actually suggests that an increased risk perception entails changes in political or civic attitudes. It is often associated with more conservative views (Lerner et al., 2003, Huddy et al., 2005) and the readiness to trade off civil liberties for enhanced security (Bozzoli and Müller, 2011). We suggest an original assessment of whether global terror is responsible for a change in voting attitudes. Given data availability, we can address this question only for a subset of countries (Germany, the US and Switzeland). We show that global terror significantly increases the intentions to vote for conservative parties during 1994-2013. Daily variation in terror intensity affects political views by possibly changing the perception of threat exposure, as reflected in SWB responses. This is corroborated by the co-movement between emotional and political responses across individual types: we find that those exhibiting larger SWB responses to terror – possibly feeling more exposed – are also more likely to experience a conservative shift. We close this study with a discussion of promising research avenues using the present approach and notably the decomposition of time periods or the extension to poorer countries and alternative outcomes. We highlight the possible use of SWB as a yardstick for determining the degree of emotional shocks that could trigger changes in behavior and attitudes towards democracy, security, minorities or migration.

2 Empirical Approach

2.1 An International Panel of Individual Well-Being

Data Selection. We construct a panel of individuals covering several countries with comparable well-being measures and determinants. We focus on a relatively homogeneous group of six rich countries: Germany, the UK, Switzerland, the Russia Federation, the US and Australia. This choice is also guided by data availability: we combine six large household panels that contain SWB information at the individual level and over a relatively long period. These datasets and the years when SWB information is available are as follows: the German Socio-Economic Panel (GSOEP, 1984-2013), the British Household Panel Survey (BHPS, 1996-2008), the Swiss Household Panel (SHP, 1999-2013), the Russian Labor Monitoring Survey (RMLS, 2000-2013), the Australian Household Income Dynamics (HILDA, 2001-2013) and the US Panel Study of Income Dynamics (PSID, 2009, 2011, 2013).[3] These datasets also contain a wealth of individual characteristics that can be used as controls in SWB equations.

We focus on 1994-2013. Datasets are collected at different periods (starting 1984 for Germany) and our time window is guided by data constraints and the relatively homogeneous treatment of all countries under study – notably the fact that key variables are missing in panels for some years and that terror data is not available for 1993. Note that some countries offer better coverage than others: for instance, all of the relevant information is available in the GSOEP over the period studied but SWB information is only present in the PSID in waves 2009, 2011 and 2013. Sensitivity analyses will show that this is not detrimental to our results. In particular, significant terror effects are not driven by a particular country. Nonetheless, different observational periods across datasets prevent us from identifying time-specific heterogeneity of terror effects, e.g. before and after 9/11 (a modest attempt to elicit time variation is suggested in the concluding discussion).

Sample selection is applied uniformly to all countries. We focus on individuals aged between 18 and 75. Our baseline excludes first-generation migrants. Introducing them would bring in

[3] These datasets have been used extensively in SWB studies, for instance in Ferrer-i-Carbonell and Frijters (2004, GSOEP), Clark and Oswald (1994, BHPS), Stutzer (2004, SHP), Senik (2004, RMLS), Feddersen et al. (2016, HILDA) or Brown et al. (2017, PSID). See Powdthavee (2015) for a clear overview of existing SWB datasets and their use.

confounding factors regarding terror events possibly happening in their home country. Each person is interviewed once a year and the precise date is recorded and used to match terror information, as described below.

Measures of Well-Being. A rapidly-growing amount of evidence collected by economists and psychologists has shown that SWB is not pure statistical noise and can be validated in numerous ways (Kahneman and Krueger, 2006), notably against behavior (Benjamin et al., 2012) and more objective measures of well-being (Krueger and Schkade, 2008, Oswald and Wu, 2010). Self-reported measures of well-being provide new insights into phenomena that are difficult to apprehend with the traditional revealed preference approach (see Clark et al., 2008, and Senik, 2005). For instance, this includes the effect of unemployment (Clark and Oswald, 1994, Di Tella et al., 2001), climate change (Frijters and van Praag, 1998), air quality (Levinson, 2012), economic status (Luttmer, 2005) or decentralization (Flèche, 2017).

The SWB measure used in this study is based on the life-satisfaction question, which is usually strongly correlated with other subjective measures of well-being like self-reported happiness or composite indices of mental health (Clark and Oswald, 1994). Life satisfaction has the advantage of being present and relatively comparable across the different datasets in use, as explained in Appendix A1. The answer is reported in ascending order of satisfaction on different scales: 1-5 in the RMLS and PSID, 1-7 in the BHPS and 0-10 in the GSOEP, SHP and HILDA. We harmonize the scales across datasets by expanding the life-satisfaction answers in the PSID, the RLMS and the BHPS to 11 points. The procedure is described in detail in Appendix A1 and alternative harmonizing approaches are presented in our sensitivity checks (notably one collapsing answers to the least common denominator, i.e. the 5-point scale). The mean level of SWB for each country is reported in Table A.1, in their original scale (first row) and using the 0-10 or 1-5 harmonized scale (second and third rows). The country ordering based on mean values is consistent across scales, with the highest score reached in Switzerland and the lowest in Russia.

A usual concern among economists is the difficulty to perform interpersonal comparison of utility. SWB measures do not escape from this discussion. They possibly reflect heterogeneity in self-perception about one's situation (Decancq et al., 2015) or relativities regarding others or oneself over time (aspirations). We follow the bulk of the literature and treat this issue as a mere measurement error, namely by using large samples and accounting for fixed effects. Individual effects may capture time-invariant heterogeneity in actual well-being or in the way a person reports well-being or forms aspirations. Note that we will not only focus on the absolute effect of terror on SWB scales but also on its relative effect using equivalent-income variation (see also Decancq et al., 2015, and Benjamin et al., 2014). Finally, our estimations will control for time-varying correlates of SWB. In Appendix A1, we describe how these variables are made comparable across countries. Table A.1 reports statistics for the key variables. The main determinants of SWB, income and health, are consistent with the SWB ranking across countries: Switzerland and Russia are found to be at both ends of the distribution.

2.2 Global Terrorism Database

We use the GTD, a unique open-source dataset collected by the National Consortium for the Study of Terrorism and Responses to Terrorism. It provides comprehensive information on terror events in the world from 1970 until present (see LaFree and Dugan, 2007, for more information). There are some exceptions, including teh fact that 1993 is missing. The GTD applies a consistent definition of acts of terror, as quoted in the introduction.[4] More precisely, terror acts are defined using three non-mutually exclusive criteria. Events are recorded as terror activity if (i) they have the intention to coerce, intimidate or publicize to larger audience, (ii) they stand outside international humanitarian law as reflected in the Additional Protocol to the Geneva Conventions of August 1949 and (iii) they have political, economic, religious or social motives. This definition excludes acts motivated by individual profit or unrelated to broader societal change. In particular, hate crimes or mass shooting in the US – which most often lack a clear political or social motivation – are not included. The immense majority of the 70, 118 terror acts recorded over the period take place abroad (i.e. only 4.4% take place in our sampled countries: 1.6% in the five Western countries and 2.8% in Russia).[5]

Figure 1 displays the number of terror events and casualties per day. Figure 2 shows a distribution summary of both events and casualties.[6] The average number of events per day is 9.6 and the average daily number of fatalities is 22.5. There are several terror events occurring almost every day around the globe over the whole period. Precisely, out of the 7, 305 days between the 1st of January 1994 and the 31st of December 2013, only 3.7% were exempt from terror and 10.2% from fatalities. With such little variation at the extensive margin, we are not strongly interested in the occurrence of terror somewhere in the world on particular days. We will rather exploit the high-frequency variation in daily counts of events and casualties revealed by Figure 1 to capture the welfare impact of terror. In terms of time trends, Figure 1 points to a significant increase in terror intensity since the mid-2000s. Some have argued that global terror has intensified partly due to the counter-productive effects of the Iraq war (and the "war

[4] It is similar to other definitions of 'terrorism' like the one used in the US Code of Federal Regulations ("The unlawful use of force and violence against persons or property to intimidate or coerce a government, the civilian population, or any segment thereof, in furtherance of political or social objectives").

[5] Regarding global fatalities, 164, 423 are counted during this period, 4.5% of which concern our sample. This comprises 1.98 percentage points for the US, 2.46 for Russia and only .0007 (107 casualties) for Australia, Switzerland, Germany and the UK.

[6] Both figures are capped at 50 for clarity. Note that less than 0.5% (10%) of all days are characterized by more than 50 events (50 casualties).

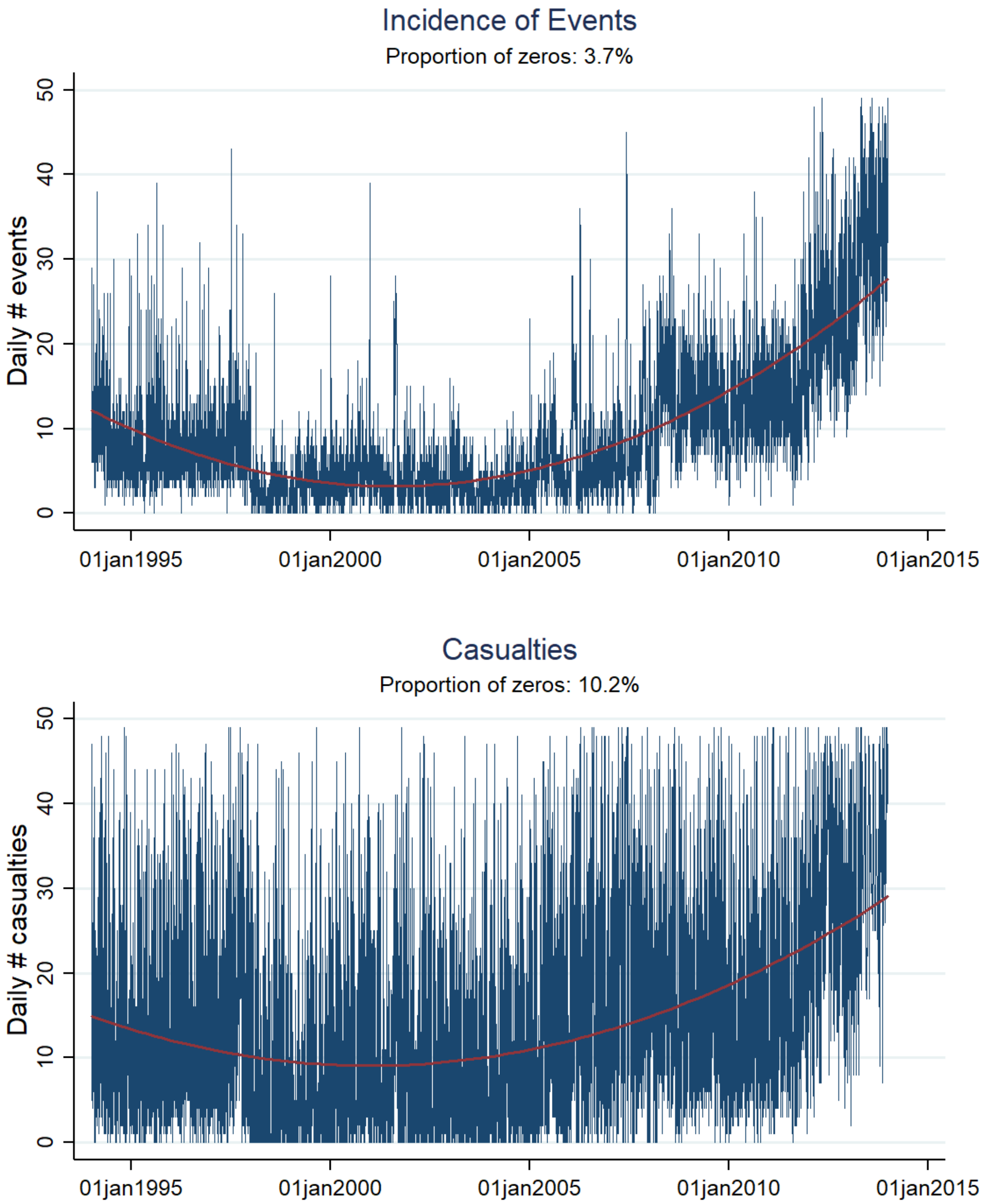

Figure 1: Daily Events and Casualties over 1994-2013

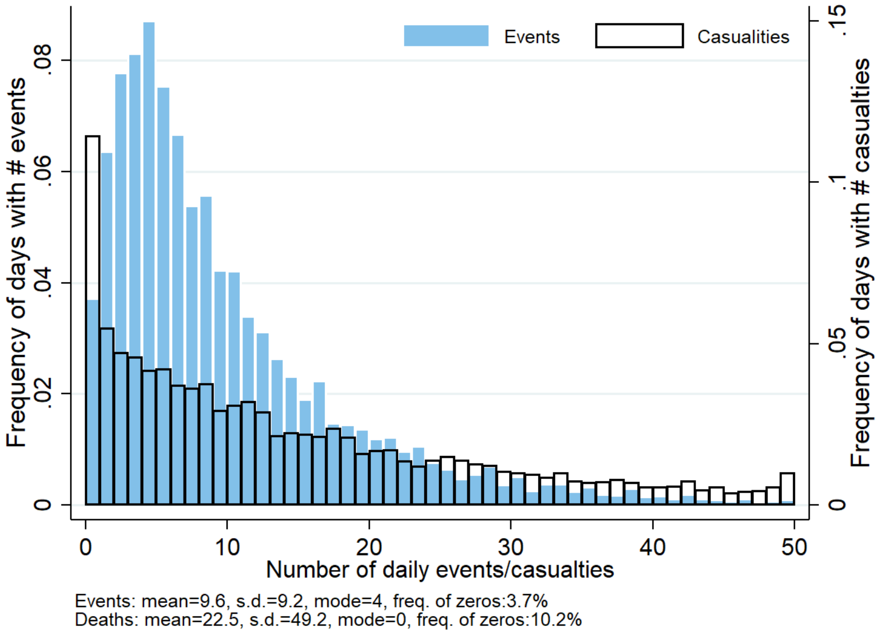

Figure 2: Distribution of Events and Casualties over the 7,305 Days during 1994-2013

on terror") from 2003 onwards, although evidence is unclear (Harrow, 2010).

Beyond the precise terror act criteria mentioned above – which can be controlled for in our estimations – a complete set of information is provided in the GTD, including the nature of the events, their location, the number of persons wounded or killed, the type of attack (e.g. hijacking, bombing), the type of target (e.g. embassy, civilians) and the purpose (e.g. political, religious). We display the geographical distribution of terror intensity in Figure A.1 in the Appendix. Terror incidences and fatalities are widespread around the world during the period under study. We complete the portrait of terror in Table A.2, with the total number of events, the daily average fatalities/incidences and the breakdown by main attack characteristics overall and by country. The main medium of attack is explosion-bombing (51% of all events, responsible for 46% of all casualties), which sharply increases during the period. We also see that extended events (lasting more than 24 hours) – which may be more difficult to match with interview days – represent only a minority (5%). The table provides statistics by years and broad regions of the world. The majority of events (64%) are located in South/Central Asia and Middle East/North African countries.

2.3 Empirical Strategy and Identification

Empirical Approach. We merge each (person × interview date) observation of the international panel dataset with information on the terror events that occurred the previous day in the world, given the time zone where the person is located. Identification is based on short-term fluctuations in well-being and terror intensity. It is similar to the valuation of time-varying local public good such as air quality in Levinson (2012), who matches daily self-reported happiness and air pollution information. In our case, we value a global bad – terror – assuming that the SWB recorded on day d in our panel is affected by terror events taking place on day $d-1$. The previous-day assumption aims to ensure visibility of the event, and full informational coverage, although we will investigate the sensitivity to alternative matching assumptions.

The specification of the empirical model goes as follows. We estimate the life satisfaction of individual i recorded on year t and date d (day/month) as:

$$W^*_{itd} = \beta T_{td-1} + X_{itd}\alpha + \theta_t + \mu_d + \varphi_i + \varepsilon_{itd}. \tag{1}$$

The latent well-being W^*_{itd} is considered as a proxy for the unobserved welfare of a person, for which we observe an ordinal metric $W_{itd} = j$ on an ordered scale of life-satisfaction categories $j = 1, ..., J$. Our baseline estimation approach comprises linear panel estimations of the ordinal measure $W_{itd} = j$, treated as as a continuous variable, with the $J = 11$ points scale.[7] The main covariate is the intensity of terror the day before the interview, T_{itd-1}. As discussed, we principally focus on two definitions of terror intensity, namely the number of global terror *incidences* and the number of *fatalities* on day $d-1$. We compute T_{itd-1} as $log(terror\ intensity + 1)$, although our conclusions show little sensitivity to the specification, given the very low rate of zeros. The treatment effect β is our key variable of interest, which we estimate in separate regressions for incidences and fatalities. We include several controls. We account for individual time-varying characteristics of individual i that may influence well-being at the time of observation (year t, date d), X_{itd}.[8] Year dummies θ_t may pick up the effect of global shocks on well-being that are common to all countries in each year. More flexible specifications using country or region-specific time trends hardly affect our results. Month dummies μ_d may capture seasonality in data collection (periods during which interviews are conducted) as well as seasonality in SWB (e.g. people could be happier in spring or summer time). Individual

[7]Linear estimations treating j as a continuous variable ease the inclusion of panel fixed effects. Previous studies show no appreciable difference between estimating SWB models with linear or latent dependent variable specification (Ferrer-i-Carbonell and Frijters, 2004). Nonetheless, we will provide checks where we acknowledge the ordinal nature of the dependent variable.

[8]These are the usual determinants of SWB, including marital status, family characteristics (household size and number of children), log household income, work status, self-assessed health and education (age and gender are picked by fixed effects). We also account for region dummies, which are country-specific by definition, but not necessarily captured by individual fixed effects due to the fact that some people are geographically mobile over the course of the panel. We use the 16 Federal States (Länder) of Germany, the 13 regions in the UK (9 English regions, Wales, Scotland, Northern Ireland), the 26 Cantons in Switzerland, a detailed classification of 13 Australian regions (constructed using information on state or territory of residence and population density), 40 political regions in Russia, and the 50 Federal States in the US.

heterogeneity φ_i is modeled as fixed effects in panel estimations. As discussed, they control for time-invariant heterogeneity in well-being or the perception of life circumstances. In our context, they may also be correlated with time-invariant individual characteristics related to the perception of terror and exposure to threats (for instance, risk aversion or the propensity to experience fear or compassion, which may lead to disruption in panel interviews, as discussed below).

Identification. Cross-sectional variation in terror intensity is sufficient to identify the effect of terror intensity. For an illustration, let us focus on a particular day $d-1$ characterized by high terror intensity. Take two sets of persons i and i' interviewed just after and before that day respectively:

$$W^*_{itd} - W^*_{i'td-2} = \beta(T_{td-1} - T_{td-3}) + (X_{itd} - X_{i'td-2})\alpha + (\varphi_i - \varphi_{i'}) + (\varepsilon_{itd} - \varepsilon_{i'td-2}). \qquad (2)$$

Identification relates in spirit with a regression discontinuity (RD) design since we exploit treatment heterogeneity around a (time) cutoff. In this example, the treatment effect β captures the change in terror intensity around a particular date, for instance generated by $T_{td-1} > T_{td-3} \approx 0$. However, we exploit more than a switch from no event to some event. Here, we avail of the high-frequency fluctuation in terror intensity generated by the flow of terror events ($70,000$ events) over $7,305$ days. In our example, confounding events are not an issue since identification implicitly relies on individuals observed just around the time threshold. For instance, it is very unlikely that confounding factors (like bad politics) may codetermine SWB-depressing events (like bad social/economic conditions) and violent acts, at least not in the short lapse of time around every terror event recorded in our sample. Moreover, the immense majority of world terror events take place abroad, rather that in the countries under study, so that they can be considered as relatively exogenous to local well-being conditions. The only issue that we can think of pertain to potential non-random attrition in interviews, which is extensively discussed hereafter.

The 'between' identification established above is similar to Levinson (2012). We can go a little further. With panel information, time variation between two years t and $t-1$ allows purging estimations from individual fixed effects φ_i. Cross-sectional variation around each day of potential terror is therefore completed by time-demeaning as in a difference-in-difference approach (or a difference-in-discontinuity). We can illustrate this in our example with individuals i and i' interviewed around the terror-intensive day $d-1$ in year t. Taking the time difference Δ between both years, and assuming negligible terror intensity around interview dates in $t-1$, we obtain:

$$\Delta W^*_{itd} - \Delta W^*_{i'td-2} = \beta T_{td-1} + (\Delta X_{itd} - \Delta X_{i'td-2})\alpha + (\Delta\varepsilon_{itd} - \Delta\varepsilon_{i'td-2}). \qquad (3)$$

Accordingly, the effect of global terror T_{td-1} is identified from cross-day comparison while purging the estimation from individual effects. To pursue the analogy with RD designs, note that the persons observed around the (time) cutoff are as good as random, so that *we expect individual fixed effects to play a limited role in our identification.* Finally, let us stress again that this example is only an illustrative zoom on a particular day. Our global terror effect is identified by the fluctuation in terror intensity over 7,305 days and a multitude of events.

Non-Random Selection into Interviews. Identification does not require terror to occur randomly. In fact, the GTD data shows a relatively uniform distribution of terror events throughout the years, as reported in the first column of Table A.3 in the Appendix. It is nonetheless possible that some events – including some of the large ones – are organized on specific dates. [9] This is not an issue: we simply need the timing of terror to be independent from interview dates. Then, the remaining question is whether interviews are distributed randomly around terror events. Non-random attrition in interviews might occur if interviewees change their next-day schedule due to the terror shock and are self-selected. Since they are likely to be those most afflicted by what happened, our effect would be a lower bound of the average treatment effect. We provide four arguments to rule out any concern of this kind. *First*, fixed effects should capture much of the time-invariant specificities of these persons. *Second*, this issue should primarily concern local events while we focus essentially on events taking place beyond borders. We will show that our results hold when focusing exclusively on foreign events. *Third*, large events like 9/11 may create global shock waves that could affect the response rate of interviews planned on the next day in other countries. We will show that our results are not (only) driven by major events. *Fourth*, and most importantly, we conduct some tests in the spirit of the McCrary test for RD designs. Precisely, we check that the density of interviews does not change discontinuously around the time of large events. We use the GSOEP due its broad time coverage, which allows performing density tests for events occurring at different points in time. For illustration, we focus on 9/11, the 2004 Madrid attacks and the 2005 London attacks. Appendix Figure A.2 shows no sign of disruption in GSOEP interviews following these three salient events. This should a fortiori be true for smaller events. We verify this by running density tests over all the days (and countries) in our data.[10]

[9] Some violent acts occur on days that actually coincide with other newsworthy (and anticipated) events in order to minimize news coverage (Durante and Zhuravskaya 2018). By contrast, others are planned to maximize the coverage of terror in the media of targeted countries (Weimann, 2005) or influence the next day elections (Montalvo, 2011), for instance. On the non-random timing of terror, see Pape (2003).

[10] For each day in our 20-year sample, we run a regression of the number of daily interviews over a one-month bandwidth around that day. We use a cubic spline specification and a dummy for a potential discontinuity on this day. From this large series of estimations, we obtain a uniform distribution of the p-values for the potential discontinuity in interview rates, and a .50 average p-value. Less than 5% of the days generate a significant drop in density ($p < .05$): further regressions show that these cases are unrelated to the previous day (or same day)

Power and the Distribution of Events/Interviews over Time. The power required to identify the effect of a particular event pertains again to the spirit of a RD design: a sufficient number of observations is needed just before and after this event. This is the requirement in Metcalfe et al. (2011) who focus on a unique event. It is considerably relaxed in our setting. We exploit an extremely large number of events throughout the period, hence we benefit from repeated day differentials of similar intensity. Nonetheless, our estimate would not be representative of the average world terror intensity during 1994-2013 if interviews were insufficiently spread over each year. This would particularly be the case if terror events showed strong seasonality, leading to a mismatch with the periods during which interviews take place. Reassuringly, as already pointed out, Table A.3 reveals a relatively uniform distribution of terror events over the year (first column). Besides, there is a fairly large overlap with the months during which interviews took place (second column). Even if there is some seasonality in the distribution of interviews within countries, a large number of observations is available at each point in time throughout the year.

2.4 An Intuition of the Results

Before moving to the estimation results, we can provide a graphical illustration of the causal relationship between welfare levels in the six countries and global terror intensity. We first clean observations from common year effects and individual fixed effects (to improve SWB comparability and purge from factors like country fixed effects). We take the residual of a basic regression $W^*_{it} = \theta_t + \varphi_i + u_{it}$ as our individual welfare measure, which we plot against terror intensity. Rather than showing every data point on a crowded graph, or even the mean values of each of the $7,305$ days, we group observations into equal-sized bins. Figure 3 displays the binned scatterplot, i.e. the bin average values of welfare and terror intensity, as well as the trend line. With both the incidents and fatalities, we observe a clear negative relationship between welfare and global terror. This pattern is very suggestive but shows only a correlation. As demonstrated above, micro regressions will capture a causal link between well-being and global terror using 'between' variation in terror intensity. Days of particularly intensive world terror pervade Western lives and create welfare shocks, which are susceptible to have further consequences on attitudes and behavior, as we shall see.

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terror intensity.

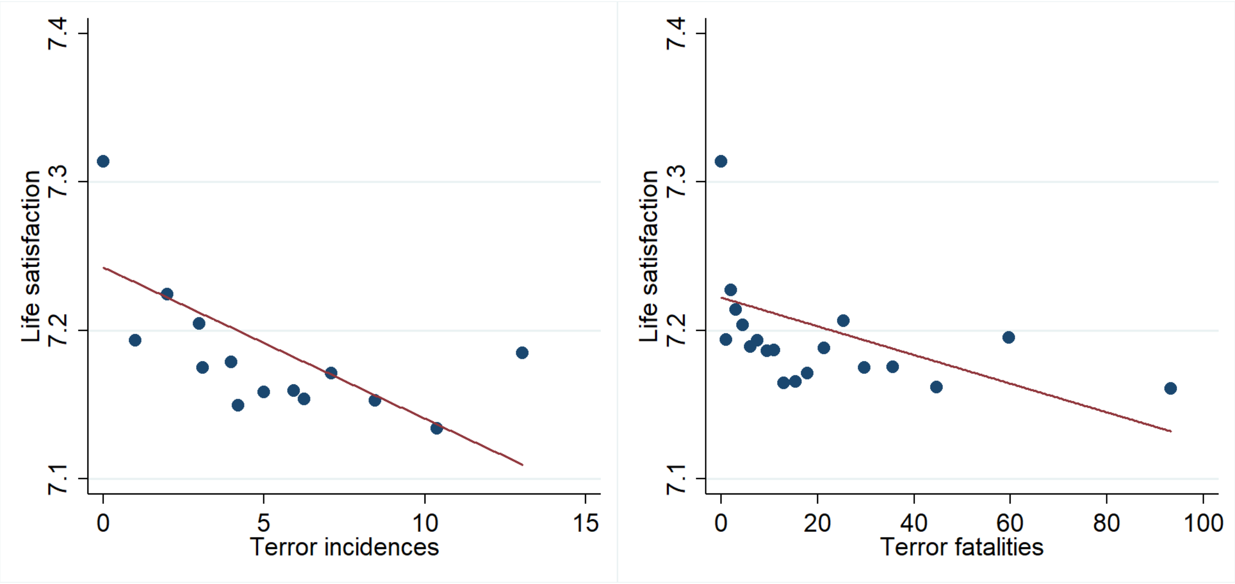


Figure 3: Well-Being and Global Terror, 1994-2013

3 The Welfare Effect of Global Terror

3.1 Baseline Results

We first present our main results, namely the estimation of model (1) on our six-country panel data. It relates the daily intensity of global terror to individual SWB in these countries, conditional on various individual and family circumstances. We also address the sensitivity of our results to a battery of checks using alternative estimation methods, alternative measures of SWB or terror intensity, alternative specifications and alternative timings of events.[11] All tables of estimates that follow report the coefficients on log terror intensity β and, for the purpose of equivalent income calculations, the coefficient $\alpha^{\ln y}$ on log household income.[12]

Global Terror Effect. Our main results are presented in the first column of Table 1. We use linear panel estimations with fixed effects, treating the 11-point measure of life satisfaction as a continuous variable. The intensity of terror – whether the number of events or the number

[11] In all specifications, standard errors are clustered at the year $\times$ country level to account for error autocorrelation across citizens of the same country. We have alternatively clustered at the time $\times$ region level or at the individual level. Given the very large sample size, standard errors only slightly increase in these cases and our conclusions remain unchanged.

[12] The complete set of life-satisfaction estimates is available from the authors. It shows very standard results (as surveyed in Clark et al., 2008). Essentially, income, good health and being married are positively related to SWB while being unemployed is negatively correlated. The impact of these variables is very comparable and stable across countries, an interesting regularity discussed in the literature (e.g. Akay et al., 2017).

of fatalities – depresses individual welfare in a very significant way.[13] Notice that a higher intensity of terror may imply a higher chance of being informed and hence of being exposed. We investigate the potential non-linearity of the terror effect. We use dummies for the second, third and fourth quartiles of terror intensity (in turn for incidences and fatalities). Table 1 reports their effects relative to the first quartile. For both incidences and fatalities, we observe a consistent monotonic relationship: the response gradually increases with terror intensity. Arguably, in the case of fatalities, effects in quartiles 2 and 3 are not very different from each other, while the effect of quartile 4 is much larger. Most importantly, for both measures, all quartiles 2-4 are very significant, which conveys that our average effect is not only driven by days/events of exceptionally high terror intensity. Alternative unreported estimations also confirm that our average effect does not vary much when taking out extreme points (like 9/11, which is the largest event with 3,003 fatalities). As previously discussed, these checks are also important if large events like 9/11 were to affect the timing of interviews in a non-random way.

Table 1: Welfare Impact of Global Terror: Baseline Results

	# Terror Incidents or Fatalities (log)	Quartiles of Terror Incidence or Fatalities		
		Q2	Q3	Q4
Terror Incidence (log)	-0.0148 ***	-0.0102 ***	-0.0193 ***	-0.0268 ***
	(0.0026)	(0.0038)	(0.0043)	(0.0051)
Household Income (log)	0.0849 ***		0.0849 ***	
	(0.0029)		(0.0029)	
Terror Effect: Equivalent Income	-0.174	-0.12	-0.23	-0.32
R-Squared	0.077		0.078	
Terror Fatalities (log)	-0.0076 ***	-0.0106 ***	-0.0110 ***	-0.0266 ***
	(0.0014)	(0.0040)	(0.0042)	(0.0046)
Household Income (log)	0.0848 ***		0.0849 ***	
	(0.0029)		(0.0029)	
Terror Effect: Equivalent Income	-0.090	-0.12	-0.13	-0.31
R-Squared	0.077		0.078	
#Observations	750,691		750,691	

Linear estimations of life satisfaction on incidences or fatalities (log #, dummy or quartiles). Models control for age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence (the 16 Federal States of Germany, the 13 regions in the UK, the 26 Cantons in Switzerland, a detailed classification of 13 Australian regions, 40 political regions in Russia, and the 50 Federal States in the US) and individual fixed effects. Clustered standard errors are presented in parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.

[13] Unreported standardized coefficients indicate that a one standard-deviation increase in incidents (fatalities) is associated with a decline of 0.6% (0.5%) of a standard deviation in SWB. While this may seem modest, it reflects the huge cross-sectional variance in SWB and is very much in line with the literature. For the largest event (the 9/11 attacks), Metcalfe et al. (2011) report a point estimate of the effect of 5%– 9% of a standard deviation in mental health.

Note that the average effect reported in Table 1 can be interpreted as the impact of an average day of global terror over twenty years. Every day, everyone is treated: both the 'control' individual interviewed before that particular day and the 'treated' person interviewed just after. We simply observe them at different points in time for inference. Thus, everyone is constantly treated by a flow of world terror of varying intensity.[14] The effect of mean terror intensity may be smaller at the end of the period under study, if a long-term habituation to terror news exists. It may also be lower, if awareness/exposure increases through more aggressive media coverage (or the emergence of social media) in the recent years. While we are not able to explore this question with the data at hand, we touch upon time variation in the concluding section.

Equivalent Income. Since log income is included in our empirical model, we can assess the magnitude of the terror effect by computing an *equivalent income* variation. SWB has been used for some time to obtain money metric measures of public goods (e.g. air quality, Levinson, 2012) or public bad (e.g. unemployment, Di Tella et al., 2001). We suggest the first equivalent income measure of global terror. With a specification whereby terror intensity and income enter in log terms, it is easily shown that $\beta/\alpha^{\ln y}$, the coefficient of log intensity over that of log household income, is an equivalent income elasticity. As reported in Table 1, we obtain an elasticity of $-.17$ ($-.09$) with incidences (fatalities), i.e. a 1% increase in the count of terror events (fatalities) is equivalent to a 0.17% (0.09%) decrease in household income. With an infra-marginal interpretation, these figures actually tell us that the complete elimination of global terror would require giving away a large share of one's income, namely between 9% and 17%.

Comparisons. It is useful to provide some elements of comparison despite the fact that other studies mostly look at the effect of *specific* events and the *local* welfare implications of terror. In this regard, they are expected to yield larger equivalent income effects than ours. For instance, Frey et al. (2009) compare France and the British Islands. The ferocity of the Northern Ireland conflict explains that a British resident would be willing to pay between 26% (fatalities) and 37% (incidents) of income to avoid violence, while a Parisian would be willing to forego between 4% (fatalities) and 8% (incidents). The only study considering the effect of terror abroad is Metcalfe et al. (2011). Assessing the impact of 9/11 on British mental health, they report an equivalent income effect ranging from 31% to 71% depending on modeling choices (seasonal controls or not). They advise a cautious reading of this result because, in the absence of a significant income effect, they base their calculation on a marginal utility of income drawn

[14] Since we capture the average response to this repeated 'background noise' of terror, it is difficult to speak about adaptation. The concept is more relevant when focusing on a particular event/day. For instance, previous studies have assessed the recovery time to specific events like 9/11 (Krueger, 2007) or the Boston Marathon bombing (Clark et al., 2017).

from external sources. In the present case, we obtain significant and relatively stable effects of income (we address this point later). Moreover, Metcalfe et al. focus on the extreme point of our terror event distribution (9/11). As can be seen in Table 1, equivalent income effects for the top quartile (which includes 9/11 and other large events) are $31\% - 32\%$, hence in the range of values obtained by these authors.

3.2 Sensitivity Checks

In Appendix B, we suggest an extensive series of robustness checks. We first verify whether the results are sensitive to alternative *controls* on terror regions (Appendix B.1, Table B.1). In particular, we check whether the fatality effect reflects the characteristics of the main event of the previous day (for instance, whether the emotional shock is due to the type of attack, e.g. bombing, rather than to the death toll per se). We also control for the complete set of past-day terror location dummies and, alternatively, for the physical or genetic distance to the terror countries. We find little variation compared to the baseline.

Next, we check the sensitivity of our estimates to alternative estimation *methods* (Appendix B.2, Table B.2). The results are extremely stable, in particular when acknowledging the ordinal nature of the dependent variable with a fixed-effects ordered logit estimation. Interestingly, the effect is also similar to the baseline when ignoring fixed effects (i.e. in pooled linear estimations). This is an important result: it confirms that individual unobserved heterogeneity plays a minor role and that 'between' variation around terror days is sufficient to achieve robust identification. Arguably, equivalent income effects are slightly smaller, between 6% (fatalities) and 10% (incidences), although this is almost entirely due to the larger income effect obtained in pooled estimations. The latter is intuitively explained: individuals adapt to higher income (see Luttmer, 2005), so that 'within' variation (in fixed effects estimations) is expected to be lower than 'between' variation (in pooled estimations). Notwithstanding, the coefficient on income remains in the same order of magnitude.[15]

Further, we find that the results are not very sensitive to alternative *specifications* of the model with respect to the main explanatory variables (Appendix B.3, Table B.3), notably the separate estimation of incidence and fatality effects or the use of a linear (rather than log) function of terror intensity. Our findings are also very robust to the way in which we harmonize SWB scales across countries: with the 5-point scale, the coefficients are close to half of the estimates on the 11-scale and yield very similar equivalent income effects.

Finally, we address the *timing* assumptions made to match terror and interview days (Appendix

[15]It is possible that reverse causality between income and SWB actually means that we still underestimate well-being returns to income (Luttmer, 2005). Even though, the terror effect would remain significant. Its equivalent income interpretation would simply become more modest.

B.4, Table B.4). There may be a little fuzziness in the treatment status due to the fact that individuals interviewed on terror day are implicitly counted in the control group (together with all those interviewed the days before). This should lead to a slight underestimation of our terror effect inasmuch as some of them have already been affected. With a large number of interviewees on both side of the time cutoff, this makes little difference. Note that the timing of interviews is generally recorded but the timing of terror events is unknown – or is spread over several hours – which makes the time matching difficult. Our previous-day assumption appears to be a reasonable choice and generates the largest effects, as explained in Appendix B.4.

3.3 Further Results

Terror at Home or Away. We first check whether people are more affected when terror events actually takes place on their doorstep. Table 2 reproduces our baseline (Column 1) and compares it to the effect of terror intensity within the person's own country (Column 2). As expected, local terror drives larger well-being responses, i.e. around twice as large as the baseline effect. It is equivalent in magnitude to the top quarter of global terror (see the last column of Table 1). Local terror may well have large effects, it occurs very infrequently compared to events abroad. As noted before, only 1.6% of the $70,118$ terror incidents during 1994-2013 occurred in the Western countries of our sample (4.4% when including Russia). Hence, we expect our baseline effect – the global terror effect – to be mainly driven by foreign events. This is confirmed in Table 2 (Column 3): the effect of foreign terror is highly significant and only slightly smaller than the baseline.[16]

International Variation. We then ask whether the global terror effect is universal or driven by some of our sampled countries. Given the size of the GSOEP, Germany represents 39% of our international sample. Column 4 of Table 2 shows that our results are not strongly influenced by this country: the global terror effect is smaller but still significant in the 5-country panel excluding Germany. The rest of the table reports terror effects for each country separately. As expected, terror coefficients are less precisely estimated in this case, although the estimates are relatively consistent across countries. The coefficient on terror incidence is significant in all cases except Russia. Equivalent income effects are in a range from $-.14$ (the UK) to $-.32$ (the US), hence surrounding the average baseline effect of $-.17$. The US estimate stands out, at around twice as large as the average. Interestingly, this result echoes with the fact that counter-terrorism expenditures in the US are also much larger, at around twice those of other Western

[16] The difference with the local terror effect of column 2 is nonetheless significant (the p-value of an equality test between coefficients is .023 for incidence and .096 for fatalities). Compared to the local terror effect, the impact of global terror is also more precisely estimated given the larger variation in terror intensity.

countries.[17] The effect of terror fatalities is consistently smaller, as found on average, but very stable across countries. It is significant in all countries except Switzerland and the US, which is likely due to smaller samples – and hence less precise estimates – in the case of these countries (they represent only 5.4% and 3.3% of our international panel respectively). However, in equivalent-income terms, country-specific effects are all in a very narrow range from $-.05$ to $-.10$, surrounding the baseline of $-.09$.

Table 2: Welfare Impact of Local and Global Terror, Overall and By Country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All (baseline)	All Terror in own countries	All Terror in rest of the world	Without Germany	Germany (GSOEP)	United Kingdom (BHPS)	Switzerland (SHP)	Russia (RMLS)	Australia (HILDA)	USA (PSID)
# Incidences (log)	-0.0148 ***	-0.0252 ***	-0.0108 ***	-0.0095 ***	-0.0143 ***	-0.0122 **	-0.0198 **	-0.0011	-0.0122 *	-0.0270 **
	(0.0026)	(0.0056)	(0.0026)	(0.0030)	(0.0046)	(0.0048)	(0.0102)	(0.0056)	(0.0068)	-0.0129
Equivalent Income	-0.17	-0.30	-0.13	-0.11	-0.17	-0.14	-0.23	-0.01	-0.14	-0.32
# Fatalities (log)	-0.0076 ***	-0.0137 ***	-0.0064 ***	-0.0060 ***	-0.0055 **	-0.0041 *	-0.0071	-0.0052 *	-0.0083 **	-0.0047
	(0.0014)	(0.0042)	(0.0014)	(0.0016)	(0.0024)	(0.0023)	(0.0057)	(0.0031)	(0.0037)	(0.0077)
Equivalent Income	-0.09	-0.16	-0.08	-0.07	-0.06	-0.05	-0.08	-0.06	-0.10	-0.06
R-Squared	0.077	0.081	0.080	0.070	0.203	0.110	0.069	0.140	0.119	0.074
#Observations	750,691	750,691	750,691	449,012	301,679	140,600	40,479	134,846	108,164	24,923

Linear estimations of life satisfaction on incidences or fatalities. Models control for age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence (the 16 Federal States of Germany, the 13 regions in the UK, the 26 Cantons in Switzerland, a detailed classification of 13 Australian regions, 40 political regions in Russia, and the 50 Federal States in the US) and individual fixed effects. Clustered standard errors are presented in the parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.

4 Diffusion Channels and Exposure

The depressing effect of global terror can be interpreted as 'selective' compassion, anger or, most likely, fear (Becker and Rubinstein, 2011). The diffusion mechanism can involve multiple factors. In this section, we use heterogeneity *across days* to investigate the role of different channels: stock markets, anticipations of future economic losses, standard media and social media. We merge our panel datasets with data sources on stock prices, international economic relationship and media coverage, among others. We show in particular that economic channels play a relatively minor role, while media coverage by prominent TV channels filters the most salient events (but not all of the terror signal). Then, we emphasize the role of physical, genetic and cultural proximity to the regions and victims of terror, and show how the terror effect increases when people feel more exposed or involved.

[17] These calculations based on the 'Stockholm International Peace Research Institute' database, cf. www.sipri.org

4.1 Economic Channels

Markets. Global terror may affect sectors that are key for national development (Abadie and Gardeazabal, 2003). In terms of SWB response to terror, actual damages to the real economy take time to materialize. A more rapid signal may go through stock markets. Several studies have investigated the impact of terror on stock prices (Abadie and Gardeazabal, 2003, Straetmans et al., 2008) and commodity prices (Guidolin and La Ferrara, 2010). Other studies, in particular Deaton (2012) and Frijters et al. (2015), have shown that SWB closely tracks the stock market index over time.[18] We attempt to connect these two causal channels for our interpretation by checking whether terror events impinge on well-being through their effect on stock prices. Expected losses may be associated with a decline in portfolio value. The consequences of terror may also be broader than this direct wealth effect, since most people do not have financial interests in the stock market. As argued by Deaton and Frijters, stock markets have become the leading indicator of what is happening locally and globally. In particular, they reflect expectations about key outcomes like employment prospects (Frijters et al. 2015).

In order to shed some light on this mechanism, we collect daily information on a variety of international market indices I_{td} that we introduce in our controls.[19] In Table 3, we include in turn the following indices: (i) the Dow Jones global index, (ii) stock market closing prices for each country (the S&P/ASX 50 for Australia, the DAX for Germany, the MOEX for Russia, the SMI for Switzerland, the FTSE 100 for the UK and the Dow Jones for the US) and (iii) the international price of gold, in its capacity of store of value. The parameter estimates of terror intensity are slightly smaller, indicating that some of the signal of terror may pass through stock and commodity prices.[20] Again, this is more likely to reflect the role of market as conveying short-run anxiety about the future than a specific effect on well-being through personal portfolios. The correlation between terror and stock market fluctuations remains modest: market price daily fluctuations carry between 1% and 22% (0% and 17%) of the terror incidence (fatalities) effect.[21] As expected, the largest effects are generated by local stock indices rather than a general stock index like the Global Dow.

Anticipations of Economic Impacts. Several studies have addressed the global implications of terror through its effect on trade (Blomberg and Hess, 2006, Egger and Gassebner,

[18] Deaton uses high frequency data from the US Gallup Survey and the S&P 500 over the years 2008-2010. For Australia, Frijters et al. (2015) mobilize 12 years of HILDA data and the All Ordinaries Index.

[19] Similar results are obtained when using daily variation $I_{td} - I_{td-1}$ in the estimations.

[20] We indicate the drop in the terror coefficients as calculated relatively to baseline estimates on the reduced samples used here (stock markets data is not available for some years in the 1990s).

[21] Note that both stock markets and well-being are influenced by seasonality (seasonal affective disorder, see Kamstra et al., 2003), which is accounted for by month dummies. We have also used Hodrick-Prescott filter to eliminate seasonal fluctuations, which does not affect the coefficient on terror intensity. Detailed results available from the authors.

Table 3: Welfare Impact of Global Terror: Controlling for Stock Fluctuations

	Incidences	Fatalities		Incidences	Fatalities
Controls: international markets			Controls: Economic Relationship with Terror Regions		
Global Dow (a)			Imports and exports with terror country		
Terror Effects	-0.0115 ***	-0.0062 ***	Terror Effects	-0.0137 ***	-0.0067 ***
	(0.0026)	(0.0014)		(0.0027)	(0.0014)
Equivalent Income	0.14	0.07	Equivalent Income	0.16	0.08
Variation to baseline	-15%	-6%	Variation to baseline	-1%	-3%
#Obs.	741,376		#Obs.	708,664	
Local stock market prices (b)			Biliteral FDI with terror country		
Terror Effects	-0.0098 ***	-0.0053 ***	Terror Effects	-0.0166 ***	-0.0066 ***
	(0.0026)	(0.0014)		(0.0033)	(0.0017)
Equivalent Income	0.12	0.06	Equivalent Income	0.20	0.08
Variation to baseline	-22%	-17%	Variation to baseline	-1%	-8%
#Obs.	727,311		#Obs.	471,326	
International gold prices (ounce)			Exchange rates (relative to Japanese yen)		
Terror Effects	-0.0131 ***	-0.0066 ***	Terror Effects	-0.0127 ***	-0.0067 ***
	(0.0026)	(0.0014)		(0.0026)	(0.0014)
Equivalent Income	0.15	0.08	Equivalent Income	0.15	0.08
Variation to baseline	-1%	0%	Variation to baseline	-4%	1%
#Obs.	741,376		#Obs.	741,376	

Linear estimations of life satisfaction on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Clustered standard errors are presented in parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively. Variation to baseline is the change in terror effect coefficients relative to the baseline obtained on the same (possibly reduced) sample.

Source for market indices: www.bloomberg.com

(a) Global Dow: Global version of the Dow Jones Global Industrial Average (W1100), including 150-stock indices of corporations from around the world

(b): Australia: S&P/ASX 50, Germany: DAX, Russia: MOEX, Switzerland: SMI, UK: FTSE 100 Index, US Dow Jones.

2005, Mierrieks and Gries, 2013) and FDI (Abadie and Gardeazabal, 2008). Another possible effect is therefore the depressing effect of anticipated losses if terror impairs economic activity with key trading partners.[22] We suggest additional estimations that control for E_{t+1}, the lead levels of economic exchange between the observation country and the main terror country of the previous day.[23] The intensity of bilateral economic relationships is first proxied by the annual trade volumes (exports and imports) from the World Input-Output Tables. We also focus on levels of bilateral foreign direct investments (FDI) as reported by the OECD (only Russia is excluded due to insufficiency information).[24] The right panel of Table 3 shows that terror effects barely change when we include potential expectations of the economic consequences of terror.

4.2 Media Channels

Media Coverage. Traditional and social media are the most obvious channel that may convey information about world terror to the citizens of our sample. For a subgroup of countries (Germany, the US and the UK) and the 2001-2013 period, we avail of information from a media research institute (Media Tenor International), which collects daily data on the main TV channels and newspapers in these countries. We extract the number of broadcasted news covering a terror event that happened on $d-1$.[25] We then control for a dummy Z_{td} equal to 1 if at least one terror event was covered in these media. As seen in Table 4 (top-left quadrant), this 'media coverage' variable has a very significant effect. Its coefficient varies only a little when terror intensity is jointly introduced in the model. Indeed, media coverage by the most salient TV channels is not only a function of how dramatic the day was. It carries additional and more qualitative information about terror events and tends to filter the key events that are most likely to interest a Western audience. In fact, only one-quarter of all global terror events are reported on the main TV channels.[26] Media coverage is therefore a proxy for 'close' events.

[22] The effect will be all the larger as there is a likely economic impact to be expected and/or also because this reveals a specific proximity to terror regions – other non-economic forms of proximities (cultural, religious, etc.) are checked in what follows.

[23] Time-demeaned estimations hence account for the forthcoming variation $E_{t+1} - E_t$ in economic exchanges that may affect SWB at time t if individuals correctly anticipate potential losses. Similar results are obtained when explicitly introducing $E_{t+1} - E_t$ in the model (which yields $E_{t+1} - E_{t-1}$ in time-demeaned form).

[24] Trade volumes are drawn from www.wiod.org and FDI volumes from https://data.oecd.org

[25] It is based on a count of all TV appearances from the evening news of day $d-1$ or the morning news of day d (time imputation is made, when possible, on the basis of the program's name, for instance "ABC World News Tonight" or "CBS Evening News"). Data has been acquired from http://us.mediatenor.com/en/ and includes 6 major channels for the UK, 8 for the US and 12 for Germany.

[26] Additional estimations using terror dummies together with the media coverage dummy show that the former capture the base effect while the latter reflects the surplus characterizing the key news filtered by prominent media, making it of a similar order of magnitude as the impact of local terror or that of the top quartile of global terror events.

We suggest a more extensive analysis of proximity to terror hereafter.

Table 4: Heterogeneous Welfare Impact of Global Terror: Media Use and Media Terror Coverage

	Incidences	Fatalities		Incidences	Fatalities
Controlling for media coverage of (any) terror event:			Terror effects with indiv. heterogeneity: TV watching:		
Terror Effects	-0.0150 ***	-0.0067 ***	Daily	-0.0169 ***	-0.0078 ***
	(0.0038)	(0.0020)		(0.0050)	(0.0024)
Variation to baseline	-5.7%	-6.9%	Less frequently	-0.0123	-0.0007
				(0.0081)	(0.0043)
Media Coverage (=1)	-0.0285 ***	-0.0284 ***			
	(0.0069)	(0.0069)	difference (p-value)	0.5998	0.1257
#Obs.	359,354	359,354	#Obs.	223,502	223,502
Terror effects with daily heterogeneity in media coverage:			Terror effects with indiv. heterogeneity: internet use:		
Covered	-0.0208 ***	-0.0099 ***	Daily	-0.0150 ***	-0.0089 ***
	(0.0064)	(0.0035)		(0.0049)	(0.0027)
Uncovered	-0.0127 ***	-0.0052 **	Less frequently	0.0001	-0.0042
	(0.0041)	(0.0022)		(0.0077)	(0.0045)
difference (p-value)	0.221	0.221	difference (p-value)	0.0566	0.3313
#Obs.	359,354	359,354	#Obs.	234,934	234,934

Linear estimations of life satisfaction on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence), and individual fixed effects. Left panel: Media coverage is a variable constructed from the Media Tenor International database about daily TV media coverage in Germany, the US and the UK, which indicates whether at least one global terror event from the past day appeared in TV news (it is available for Oct 2001-2013 only). Right panel: TV use is available in our micro data for Germany: 1995, 1998, 2003, 2008, 2013; Australia: 2012; UK: 1997-2008; Switzerland: 2010, 2013. Internet use is available for Germany: 2000, 2003, 2008, 2013; Australia: 2010-13; UK: 1997-2008; Switzerland: 2001-08, 2010, 2013; Russia: 2003-13. Clustered standard errors are presented in parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively. Variation to baseline is the change in coefficient relative to the baseline obtained on this reduced sample.

Next, we estimate a model with heterogeneous effects whereby terror intensity is interacted with the media coverage dummy, i.e. βT_{td-1} is replaced by $\{\beta^{cov} Z_{td} + \beta^{uncov}(1 - Z_{td})\} T_{td-1}$. According to the bottom-left quadrant of Table 4, the effect is around one-third higher (a quarter lower) than the baseline terror effect when previous day terror has (not) received media coverage. Interestingly, terror incidence is still highly significant on days without coverage: the 'background noise' of terror still pervades Western households, possibly through other sources of information including alternative TV programs (not recorded in our media data), social media and indirect sources of information (like stock markets).

Media Use. For all countries except the US, and for a subset of years, we also avail of individual information about the use of traditional media (daily hours of TV watching) and social media (daily hours of internet use). Table 4 (top-right quadrant) shows that daily TV watchers are most affected by terror. For others, the coefficient on terror incidences is insignificant, probably due to the smaller sample size, although it is still close to the baseline. Also, we cannot reject equality of the coefficients for frequent and less frequent watchers. This result is consistent with the fact that other informational sources matter. Table 4 (bottom-right quadrant) shows more contrasted effects between daily social media users and others in the case of incidences. Given the smaller sample size, these estimates are less precise and should be taken with caution, especially given that (i) individual behavior regarding media use is possibly correlated with personal characteristics determining well-being or the perception of potential terror threats, (ii) such behavior may change over time (while we infer an average effect from varying terror intensity over 20 years).[27]

4.3 Proximity to Terror Regions/Victims

We have suggested that specific, more proximate events generate stronger emotional responses (for instance those occurring locally or those filtered by Western media). We provide further evidence along these lines. In Table 5, we report heterogeneous effects based on physical, genetic, cultural and religious distance between observed individuals and terror regions/victims.[28] Genetic distance is obtained using the data of Spolaore and Wacziarg (2016); this measure is considered to be an alternative proxy for cultural similarity since genetically similar populations share common cultures over history. We also define cultural proximity as belonging to Western (versus non-Western) populations. Since our sample countries are all predominantly Christian, religious proximity is approached by the high (versus low) rate of Christians or the low (versus high) rate of Muslims. We consider the proximity to the countries of terror or, alternatively, to the nationality of the largest group of victims. For each dimension, we indicate the p-value of an equality test between heterogeneous effects (H_0: $\beta^{close} = \beta^{far}$). The overall picture is relatively compelling: all forms of proximity to the terror regions/victims yield larger effects. The equality test is rejected in a majority of cases.[29]

5 Individual Heterogeneity and Voting Attitude

The previous analysis has suggested that the depressing effect of global terror varies with the perceived exposure to terror, as proxied by the proximity to events and victims. We push forward this interpretation and explore terror effect heterogeneity *across individuals*. The feeling that terror would eventually affect one's life with a non-negligible probability may be

[27] Suppose that being interviewed after a large event is the assignment to treatment, while hearing about it is the treatment. With this interpretation, the terror effect is an unbiased intention-to-treat (ITT) estimate, while the effect for media users in Table 4 is an endogeneous treatment effect. The ITT is independent from interviewees' characteristics (as conveyed by the fact that fixed effects hardly affect our results). This reasoning again applies to a single event: over the multitude of events in our data, it is very unlikely that some people remains constantly uninformed about the world news and, hence, untreated.

[28] Similar results are found when using alternatively the distance to the country/victims of the past-day events or the average distance to all past day terror events.

[29] This pattern might be interpreted as driven by higher compassion towards the targeted populations, in line with evolutionary arguments such as altruism and kin selection towards genetically close populations. Most likely, it reflects higher fear and anxiety when the threat becomes closer (or is perceived as such).

Table 5: Heterogeneous Welfare Impact of Global Terror: Proximity to Terror

	Incidences	Fatalities		Incidences	Fatalities		Incidences	Fatalities
Physical & Cultural Distance			Genetic Distance			Religious Distance		
Geographical distance to the main terror country:			Genetic distance to the main terror country:			Share of Christians among all victims:		
Close (below median)	-0.0161 ***	-0.0102 ***	Close (below median)	-0.0190 ***	-0.0102 ***	High (above median)	-0.0275 ***	-0.0099 ***
	(0.0039)	(0.0022)		(0.0040)	(0.0023)		0.0051	0.0027
Far (above median)	-0.0172 ***	-0.0039	Far (above median)	-0.0031	0.0018	Low (below median)	-0.0077	-0.0049
	(0.0059)	(0.0032)		(0.0062)	(0.0037)		0.0039	0.0023
difference (p-value)	0.843	0.055	difference (p-value)	0.006	0.001	difference (p-value)	0.000	0.080
#Obs.	705,649	705,649	#Obs.	647,102	647,102	#Obs.	699,536	699,536
Majority of victims in the main event were from:			Genetic distance to the main group of victims:			Share of Muslims among all victims:		
Western countries	-0.0226 ***	-0.0099 ***	Close (below median)	-0.0174 ***	-0.0101 ***	High (above median)	-0.0076 *	-0.0042
	(0.0034)	(0.0029)		(0.0041)	(0.0023)		(0.0045)	(0.0029)
Other countries	-0.0045	-0.0060 ***	Far (above median)	-0.0057	-0.0010	Low (below median)	-0.0181 ***	-0.0087 ***
	(0.0031)	(0.0018)		(0.0062)	(0.0036)		(0.0042)	(0.0023)
difference (p-value)	0.000	0.208	difference (p-value)	0.040	0.012	difference (p-value)	0.019	0.129
#Obs.	750,691	750,691	#Obs.	645,089	645,089	#Obs.	699,536	699,536

Linear estimations of life satisfaction on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Clustered standard errors are presented in the parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively. Physical distance distance to the main terror place is calculated using the centroid of the individual's region of residence and the exact location of terror. Genetic distance is obtained using the main genetic measure of Spolaore and Wacziarg (2016) and taking the average of each nationality.

more acute for certain types of people depending on their nature, where they live, etc. Variation in risk perception across days of different terror intensity (as characterized before) or across individual types (as seen below) may also trigger other types of responses and notably changes in behavior and attitudes. We extend our analysis to voting and test the assumption that people most afflicted by terror may also react by seeking protection in parties traditionally viewed as more conservative. Due to data limitations regarding political attitudes, we focus our analysis on three countries, namely Germany, the UK and Switzerland.

5.1 Fear Factors

Let us first focus on the left part of Table 6. We report the effect of global terror on well-being, overall and by quartiles of terror intensity, for the three-country sample. It is in line with previous results and interpretations on the broader sample. We then examine the role of potential 'fear factors': we report heterogeneous effects along different dimensions as available in the data. Older persons, i.e. above median age of 44, are more affected by global terror. The p-value shows that the age difference is significant for fatalities. Rich people, defined as the top quintile of the income distribution, respond more strongly to global terror, possibly feeling they have more to lose in terms of current material possessions or from the disruption in future income streams. Admittedly, the difference is not significant at standard levels.

The other factors are available for Germany only. We use subjective risk aversion, which has proven to be a good proxy for different dimensions of risk attitudes (Dohmen et al., 2011). It turns out that very risk-averse individuals, i.e. people in the top quintile of the 1-10 risk aversion scale, are markedly more afflicted by world terror. The effect is three times larger with incidences and the difference has a relatively low p-value with fatalities. We also test whether people react to the fact that terror occurs predominantly in urban areas. We use register information from the German microcensus at the level of 96 districts ("Raumordnungsregionen" or ROR). Using a relatively conventional threshold of 200 inhabitants per square kilometer (roughly the median), we find a significantly large effect among those living in densely populated areas. Finally, people living in areas with a high share of Muslim migrants are also more distressed: we find an effect two (incidents) to three times (fatalities) larger than for other citizens.[30] This may be indicative of the information about world terror provided by foreign neighbors or, alternatively, the fact that the fear is exacerbated by the presence of migrants from terror countries.[31] We have experimented with other characteristics (like education). They show no specific patterns except gender, which tends to indicate that women respond more strongly to terror (see also Lerner et al. 2003).

5.2 Voting Attitude

Overview. A growing body of literature addresses the effects of conflicts and terrorism on satisfaction with democracy and trust in institutions (Blanco and Ruiz, 2013), political attitudes and the tradeoff between security and democratic support (Rehman and Vanin, 2017, Bozzoli and Müller, 2011) or prejudices against minorities (Panagopoulos, 2006, Echebarria-Echabe and Fernandez-Guede, 2006). In this vein, we extend our analysis beyond welfare impacts and study the potential effect of terror on political attitudes. We investigate whether the people emotionally affected by global terror also exhibit a change in their political opinion. The social psychology literature indicates that the fear of death may lead to a move towards 'defensive conservatism' (Jost et al., 2003). This general psychological response to vulnerability salience is

[30] Note that living in districts with high share of migrants does not capture the same effect as living in densely-populated area: population density and migrant share are correlated only at .41.

[31] This latter interpretation relates to the increased tension between natives and Muslim immigrants in Western countries following increased terror events due to radical Islamist groups. While we suggest a broad time decomposition in the concluding section, we report here additional regressions whereby terror effects are interacted with dummies for 4 different groups: before/after the 9/11 2001 $\times$ high/low migrant shares. For incidents, the largest effects are found in the post-2001 period and are twice as large for those living in districts with high shares of Muslim migrants ($-.0218$, s.e. of .0118) compared to those in other districts ($-.0101$, s.e. of .0055). For fatalities, we find insignificant effects for all groups except the post-2001 group of people living in districts with a high migrant share (coefficient of $-.01326$, s.e. of .0063). We have also replicated these heterogeneous estimations when extending the sample to the US (state variation) in addition to Germany (ROR variation), and find a similar pattern.

Table 6: Heterogeneous Impact of Global Terror on Well-Being and Conservative Voting

	Life Satisfaction		Intention to Vote for Conservative Parties	
	Incidences	Fatalities	Incidences	Fatalities
Overall effect (Germany, UK, Switzerland)	-0.0186 ***	-0.0080 ***	0.0015 **	0.0006 *
	(0.0032)	(0.0017)	(0.0006)	(0.0003)
Q2	-0.0128 ***	-0.0111 ***	0.0011	0.0011
	(0.0048)	(0.0042)	(0.0009)	(0.0010)
Q3	-0.0243 ***	-0.0116 ***	0.0020 *	0.0018 *
	(0.0054)	(0.0044)	(0.0010)	(0.0010)
Q4	-0.0337 ***	-0.0279 ***	0.0023 *	0.0020 *
	(0.0064)	(0.0048)	(0.0013)	(0.0011)
#Obs.	482,758		323,303	
Heterogeneity: age (Germany, UK, Switzerland)				
Above median	-0.0189 ***	-0.0096 ***	0.0016 **	0.0008 *
	(0.0037)	(0.0020)	(0.0008)	(0.0004)
Below median	-0.0172 ***	-0.0050 **	0.0000	-0.0002
	(0.0044)	(0.0023)	(0.0010)	(0.0005)
difference (p-value)	0.7307	0.0730	0.1618	0.0931
#Obs.	482,758		323,303	
Heterogeneity: income (Germany, UK, Switzerland)				
Top quintile	-0.0227 ***	-0.0097 ***	0.0030 ***	0.0011 **
	(0.0040)	(0.0022)	(0.0009)	(0.0004)
Lower quintiles	-0.0168 ***	-0.0073 ***	0.0002	0.0002
	(0.0036)	(0.0018)	(0.0007)	(0.0004)
difference (p-value)	0.1202	0.2714	0.0008	0.0261
#Obs.	482,758		323,303	
Heterogeneity: risk aversion (Germany)				
Top quintile	-0.0248 **	-0.0142 **	0.0033	0.0028 *
	(0.0113)	(0.0062)	(0.0028)	(0.0015)
Low quintiles	-0.0087 *	-0.0023	0.0003	0.0006
	(0.0050)	(0.0027)	(0.0013)	(0.0007)
difference (p-value)	0.1796	0.0709	0.3282	0.1713
#Obs.	264,955		121,745	
Heterogeneity: local population density (Germany)				
High (>200 pers per km2)	-0.0181 ***	-0.0064 *	0.0029 *	0.0018 **
	(0.0065)	(0.0034)	(0.0016)	(0.0009)
Low	-0.0012	-0.0030	-0.0008	-0.0001
	(0.0066)	(0.0036)	(0.0017)	(0.0009)
difference (p-value)	0.0490	0.4615	0.1034	0.1108
#Obs.	235,144		108,711	
Heterogeneity: local share of Muslim migrants (Germany)				
Top quintile	-0.0211 **	-0.0118 **	0.0037 *	0.0027 **
	(0.0103)	(0.0054)	(0.0019)	(0.0012)
Low quintiles	-0.0099 *	-0.0034	0.0008	0.0007
	(0.0051)	(0.0027)	(0.0013)	(0.0007)
p-value	0.3135	0.1471	0.2510	0.1294
#Obs.	272,065		124,739	

Linear estimations of life satisfaction/conservative voting on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Clustered standard errors are presented in the parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively. Qualitatively similar results are obtained for life satisfaction when restricting the sample to observations for which voting behavior is observed. For Germany, registered information on immigration is available at the 96 counties level; the correlation between migrant shares and population density is .41. Muslim migrants are defined as those from countries that which are predominantly Muslim (more than 75%).

explained by the core conservative values of authority, stability and order providing a comforting anchor (Nail et al., 2009). Such a conservative shift is also consistent with several economic studies finding that the fear inspired by terror makes individuals more likely to vote for right-leaning parties (Berrebi and Klor, 2006, 2008, Gould and Klor, 2010, Kibris 2011, Getmansky and Zeitzo, 2014, Schüller, 2015).[32] In what follows, we originally relate the potential change in political attitudes to the varying degree of risk perception as measured by emotional responses to terror.[33]

Approach and Motivation. We rely on the question about political orientation in our German, British and Swiss panels and sum up voting intentions in favor of the right-side of the political spectrum of each country. For instance, for Germany, we add voting intentions in favor of the traditional right-wing parties (CDU and CSU) and the ultra-nationalists (NPD). The main conservative party, the CDU, is perceived as supporting stronger punishments of crimes, stronger involvement on the part of the Bundeswehr in cases of anti-terrorism offensives and tougher control on immigration. The voting intention variable is used to construct a dummy "intention to vote for conservative parties", denoted as $Cons$. We use the same identification approach as before and estimate the model:

$$Cons_{itd} = \beta^c T_{td-1} + X_{itd}\alpha^c + \theta_t^c + \mu_d^c + \varphi_i^c + e_{itd}. \tag{4}$$

Recall that the effect is driven by fluctuation in terror intensity over twenty years. Eliciting the potential change in political views would still be important if we focused on a single event/day. Indeed, elections may occur in the wake of large terror events or are possibly manipulated by attacks specifically organized a few days before the poll (as suggested in Montalvo, 2011). However, we exploit the repeated exposure to a continuous flow of events of varying intensity. Thus, the change in political attitudes may not be short-lived. Most likely, the way in which global terror alters political opinions on average over the long-period may entail deep behavioral consequences on actual voting.

Results and Interpretations. The right panel of Table 6 first reports the causal impact of terror on next-day intentions to support conservative parties in Germany, the UK and Switzerland. We see that global terror over the period has contributed to a significant rightward shift

[32]The study of Montalvo (2011) seems to show an opposite effect: the 2004 Madrid bombing would have influenced elections in favor of the socialist party, which was prone to a withdrawal of Spanish troops from Iraq. Yet it does not necessarily correspond to a left-wing shift. First, the outcome seems to be essentially due to the incumbent conservative government's handling of the attack. Second, several studies point to an increased anti-Arab sentiment and a displacement toward more conservative values and political ideals in Spain following the attack (Echebarria-Echabe and Fernandez-Guede, 2006).

[33]Note that several studies look at the link between SWB and voting, see Liberini et al. (2017) for recent evidence and more references.

in these countries. We can quantify the overall impact $\beta^c \overline{T}_{td-1}$ using the mean values for terror incidents or fatalities. It yields an overall increase in conservative vote share by around $.0018 - .0035$ percentage points, i.e. a $1.1\% - 1.9\%$ increase compared to the average over the period. Just like for welfare responses, changes in political orientation are not (only) driven by large events like 9/11: Table 6 shows that political response gradually increases with quartiles of terror intensity.

The psychology literature indicates that fear and distress can mediate political responses to terrorism through an increased perception of self-relevant threats, prompting the demand for stronger anti-terrorism policies and consistent with such a conservative shift (Lerner et al., 2003). While the evidence is mainly experimental (Nail et al., 2009), our results tend to corroborate this finding at a much larger scale if the daily variation in terror intensity used for identification is indeed interpreted as variation in the degree of perceived exposure. We can proceed a little further in this direction. First, using heterogeneity *across days*, we find larger political responses when terror concerns victims who are physically or genetically proximate (unreported), i.e. situations that were previously characterized as generating larger emotional responses. Second, using heterogeneity *across individuals*, we can establish a correspondence between those previously identified as most afflicted by terror and those who exhibit a stronger conservative shift. While we cannot exactly associate those who respond emotionally to terror with those who changed their political attitude, the co-movement based on observed heterogeneity is striking (see Table 6): conservative shifts also come from the older, richer and more risk averse, as well as those living in densely-populated areas and districts with a high share of Muslim migrants. This last set of results is strongly suggestive that a common mechanism increases risk perception – as characterized by well-being responses – and triggers a shift in political views.

6 Concluding Discussion

The literature in economics, political science and psychology essentially focuses on the local impact of terror. We originally evaluate the welfare cost of *global* terror. We construct a unique pool of panel data for 1994-2013, comprising six countries: Australia, Germany, Switzerland, Russia, the UK and the US. World terror incidences or fatalities are matched with self-reported well-being information for citizens of these countries. Identification is obtained by daily variation in terror intensity over 20 years. It hinges on the fact that the world terror is broadly exogenous to the timing of interviews. Individual fixed effects are also included using panel information, although unobserved heterogeneity has little influence on our estimates, indicating that 'between' (daily) variation in terror intensity provides robust identification. We find a large negative and highly statistically significant effect of terror incidences/fatalities on the well-being of Western citizens. This result holds overall and for most countries independently.

Heterogeneity in days of terror shows that exposure matters: effects are significantly larger when terror regions/victims are physically, genetically or culturally close to the interviewees. Proximity also relates to the way in which terror news is diffused. Stock prices carry only little information compared to traditional media. However, the background noise of terror plays a significant role even when terror events are not reported on prominent TV channels (but possibly conveyed by social media and other information sources). Individual heterogeneity also points to a larger distress effect among older and risk-averse citizens as well as those living in areas perceived as risky (e.g. urban areas or close to migrants from terror regions). Fear and anxiety may also change economic behavior. For a subset of countries, we show that those most afflicted by terror also respond by a shift in political attitudes towards conservative parties, which typically promise more homeland security and a tougher stance on terrorism.

There are two important aspects concerning these results. First, both welfare and political responses are causally obtained by high-frequency variation in terror intensity and offer good external validity given the large samples used. Second, our results are consistent with the fact that not only the direct exposure to terror, but also the mere perceived threat of terrorist attacks – even from countries far away – can affect well-being and political preferences (Getmansky and Zeitzo, 2014). In fact, the magnitude of SWB responses, and the existence of a shift in political attitudes, show how exacerbated the perception of global terror can be – we find a high money-metric cost of the global terror exerted over 1994-2013 (between 6% and 17% of average income across modeling assumptions). This is in line with the fact that risk perceptions can substantially deviate from actual risks in the case of rare events that have a large impact, like terrorist acts. This extreme-event bias is founded on different phenomena such as probability neglect (Sunstein, 2003) and the availability heuristic à la Tversky-Kahneman. It is especially striking given that the responses captured in this paper are essentially driven by events taking place abroad, with little chance to impact upon Western citizens' lives. Indeed, only 107 casualties are reported in the GTD over 20 years in Australia, Switzerland, Germany and the UK together. Most of the 3,254 fatalities counted in the US are due to only one event – namely 9/11 – and represent only 1% of the death toll from gun fires.

Something missing from our analysis is the variation *over time*. There are many interesting related questions to address in future research, for instance the extent to which fear adds up to the social and political consequence of the 2008 economic crisis. Another time analysis would disentangle the intensification of terror (highlighted in Figure 1) from the increased mediatization of terror (through global news and the accelerated use of social media).[34] Even though we have assembled the best available panel datasets over a relatively long period, we

[34] Several studies have analyzed the fact that media diffuse fear, hatred, sympathy, etc., and hence change behavior such as radical voting (Della-Vigna et al., 2014) or social capital and trust (Olken, 2009).

could not extract time trends in a convincing manner. Indeed, countries enter the panel at various points in time, so that the identification of time effects is problematic (different periods reflect the weight of specific countries). It is nonetheless possible to do so for single countries like Germany, since the GSOEP is a relatively large dataset covering a long period of time. We can offer one final result for this country, using year 2003 (Iraq war) as a turnaround point after which global terror increased dramatically (see Figure 1). We find that life satisfaction decreased by 0.5% between 1994-2002 and 2003-13 in Germany, with one-third of this change essentially explained by the sharp intensification of terror over the recent period.[35]

Further work should also expand our approach in three main directions. *First*, future studies could replicate our results for more countries and different regions of the world. Many panel datasets are now available in poorer regions. It is particularly important to establish the connection between life conditions, perceived well-being and political views in countries where the support for democratic values is weak or possibly undermined by repeated exposure to nearby terror (Blanco and Ruiz, 2013, Rehman and Vanin, 2017). *Second*, future work could apply similar methodologies to other outcomes including the tradeoff between security policies and civil liberties, the rejection of minorities or citizen views on migration policies, defense policies and military expenditure, or economic protectionism. Another set of relevant outcomes pertains to deep changes in time and risk preferences or social capital.[36] *Third*, the literature on SWB has recently emphasized the power of various SWB measures to predict a broad range of health, demographic and economic behavior (De Neve et al., 2013). Political behavior and attitudes have not received much attention in this literature. Our results suggest that significant shocks on SWB may be used as a yardstick to determine the extent of terror that is likely to generate a triggerability in political behavior or attitudes towards democracy, minorities, security or migration policies.

References

[1] Abadie, A. and Gardeazabal, J. (2003): "The economic cost of conflict: A case study of the Basque Country. *American Economic Review*, 93, 113-132

[35] For this result, we have re-run our estimation while interacting dummies for subperiods 1 (1994-2002) and 2 (2003-2013) with terror intensity. We find an effect of terror incidence $\beta_1 = -.0107$ (s.e. of .0076) for period 1 and $\beta_2 = -.0114$ (s.e.=.0056) for period 2: over time, the coefficient becomes significant but only slightly larger. One-third of the 0.5% decline in life satisfaction between the two periods is explained by the compounded effect of terror $\beta_2\overline{T}_2 - \beta_1\overline{T}_1$. A simple Oaxaca decomposition shows that almost 90% of this contribution is due to the dramatic increase in terror incidence ($\overline{T}_2/\overline{T}_1 - 1 = 80\%$).

[36] A particular challenge consists in differentiating changes in risk aversion from changes in the subjective probability of terror striking locally, i.e. a change in risk perception. This would help to better investigate the mechanism linking emotional shock and voting behavior (Huddy et al., 2005).

[2] Abadie, A. and Gardeazabal, J. (2008): "Terrorism and the World Economy", *European Economic Review*, 52 (1),1-27

[3] Akay, A., O. Bargain, K.F. Zimmermann (2017): "Home sweet home? Macroeconomic conditions in home countries and the well-being of migrants", *Journal of Human Resources* 52 (2), 351-373

[4] Becker, Gary S. and Yona Rubinstein (2011), "Fear and the Response to Terrorism: an Economic Analysis", CEP Discussion Paper No 1079

[5] Benjamin, D.J., O. Heffetz, M.S. Kimball and A. Rees-Jones (2014): "Can Marginal Rates of Substitution Be Inferred From Happiness Data? Evidence from Residency Choices", *American Economic Review*, 104(11): 3498–3528

[6] Benjamin, D.J., O. Heffetz, M.S. Kimball and A. Rees-Jones (2012): "What Do You Think Would Make You Happier? What Do You Think You Would Choose?" *American Economic Review*, 102(5): 2083–2110

[7] Berrebi, C. and E. F. Klor (2006): "On Terrorism and Electoral Outcomes," *Journal of Conflict Resolution*, 50(6), 899-925

[8] Berrebi, C. and E. F. Klor. (2008): "Are Voters Sensitive to Terrorism? Direct Evidence from the Israeli Electorate", *American Political Science Review*, 102, 3, 279-301

[9] Blanco, L. and Ruiz, I. (2013): "The impact of crime and insecurity on trust in democracy and institutions", *American Economic Review*, 103 (3), 284–288.

[10] Blomberg, SB , Hess G, and Orphanides, A (2004): "The Macroeconomic consequences of terrorism", *Journal of Monetary Economics*, 51(5), 1007–32

[11] Blomberg, S.B. and G.D. Hess (2006): "How Much Does Violence Tax Trade?", *Review of Economics and Statistics*, 88 (4), 599-612

[12] Blunk, S.S., Clark, D.E. and McGuibany, J.M. (2006): "Evaluating the Long-Run Impacts of the 9/11 Terrorists Attacks on US Domestic Airline Travel", *Applied Economics*, 38(4), 363–70

[13] Bozzoli, C. and C. Müller (2011): "Perceptions and attitudes following a terrorist shock: Evidence from the UK", *European Journal of Political Economy*, 27/1, S89-S106,

[14] Brown, J.R., J.D. Cummins, C.M. Lewis and R.Wei (2004). "An Empirical Analysis of the Economic Impact of Federal Terrorism Reinsurance." *Journal of Monetary Economics* 51:1, 861-898

[15] Brown, G., J. Gathergood and J. Weber (2017): "Relative Rank and Life Satisfaction: Evidence from US Households", SSRN electronic journal.

[16] Chernick, H. and Haughwout, A.F. (2006): "Tax Policy and the Fiscal Cost of Disasters: NY and 9/11", *National Tax Journal*, 59: 561-577

[17] Clark, A., and Oswald, A. (1994): "Unhappiness and unemployment", *Economic Journal*, 104, 648-659.

[18] Clark, A.E., P. Frijters, and M.A. Shields (2008): "Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles", *Journal of Economic Literature*, 46: 95-144.

[19] Clark, A., O. Doyle and E. Stancanelli (2017): "The Impact of Terrorism on Well-being: Evidence from the Boston Marathon Terrorist Bombing", Geary WP2017/08

[20] Cummins, J. David and Christopher M. Lewis (2003): "Catastrophic Events, Parameter Uncertainty and the Breakdown of Implicit Long-Term Contracting: The Case of Terrorism Insurance." *Journal of Risk and Uncertainty* 26:2-3, 153-178

[21] De Neve, J.-E., Diener, E., Tay, L., & Xuereb, C. (2013): "The objective benefits of subjective well-being", in Helliwell, J., Layard, R., & Sachs, J., eds. World Happiness Report 2013, New York: UN Sustainable Development Solutions Network.

[22] Deaton, A. (2012): "The financial crisis and the well-being of Americans", *Oxford Economic Papers*, 64(1): 1–26

[23] Decancq, K., M. Fleurbaey & E. Schokkaert (2015): "Inequality, income, and well-being". in: Anthony B. Atkinson & François Bourguignon (eds.) *Handbook on Income Distribution*, Volume 2A. Elsevier. 67-140

[24] Della-Vigna, S., Enikolopov, R., Mironova, V., Petrova, M and Zhuravskaya. E. (2014): "Cross-Border Media and Nationalism: Evidence from Serbian Radio in Croatia", *American Economic Journal: Applied Economics*, 6(3), 03-32

[25] Di Tella, R., R. MacCulloch and A. Oswald (2001): "Preferences over Inflation and Unemployment: Evidence from Surveys of Happiness", *American Economic Review* 91 (1), 335–341.

[26] Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. Wagner (2011): "Individual risk attitudes: measurement, determinants and behavioral consequences", *Journal of the European Economic Association*, 9/3, 522-550

[27] Durante, R. and Zhuravskaya, E. (2018): "Attack When the World Is Not Watching? International Media and the Israeli-Palestinian Conflict", *Journal of Political Economy*, forthcoming.

[28] Echebarria-Echabe, A. and E. Fernandez-Guede (2006): "Effects of terrorism on attitudes and ideological orientation", *European Journal of Social Psychology*, 36, 259-265

[29] Egger, P. and M. Gassebner (2005): "International terrorism as a trade impediment?", *Oxford Economic Papers*, 67(1), 42–62

[30] Feddersen, J., R. Metcalfe and M. Wooden (2016): "Subjective wellbeing: why weather matters", *Journal of the Royal Statistical Society A*, 179(1), 203–228

[31] Ferrer-i-Carbonell, A. and Frijters, P. (2004): "How important is methodology for the estimates of the determinants of happiness?", *Economic Journal*, 114: 641-659.

[32] Fleche, S. (2017): "The Welfare Consequences of Centralization: Evidence from a Quasi-Natural Experiment in Switzerland", r&r for the *Review of Economics and Statistics*

[33] Fleischer, A. and Buccola, S. (2002): "War, Terror and the Tourism Market in Israel", *Applied Economics*, 34(11), 1335–43

[34] Frey, B.S., Luechinger, S. and Stutzer, A. (2007): "Calculating Tragedy: Assessing the Costs of Terrorism." *Journal of Economic Surveys*, 21(1), 1-24.

[35] Frey, B.S., Luechinger, S. and Stutzer, A. (2009): "The life satisfaction approach to valuing public goods: The case of terrorism", *Public Choice*, 138, 317–345

[36] Frijters, P. and B.M.S. van Praag (1998): "The effects of climate on welfare and well-being in Russia", *Climatic Change*, 39, 61-81

[37] Frijters, P., D.W. Johnston, M.A. Shields, K. Sinha (2015): "A lifecycle perspective of stock market performance and well-being", *Journal of Economic Behavior & Organization*, 112, 237-250

[38] Getmansky, A. and T. Zeitzoff (2014): "Terrorism and voting: The effect of rocket threat on voting in Israeli elections", *American Political Science Review* 108(3): 588–60

[39] Gould, E. D. and Klor, E. F. (2010): "Does Terrorism Work?, *Quarterly Journal of Economics* 125(4), 1459-1510

[40] Guidolin, M. and E. La Ferrara (2010): "The economic effects of violent conflict: Evidence from asset market reactions", *Journal of Peace Research*, 47 (6), 671-684

[41] Harrow, M. (2010): "The effect of the Iraq war on Islamist terrorism in the West", *Cooperation and Conflict*, 45(3), 274 - 293

[42] Henning F. and O. Listhaug (2013): "It can happen here: the impact of the Mumbai terror attacks on public opinion in Western Europe", *Public Choice* 156, 213-228

[43] Huddy, L., S. Feldman, C. Taber and G. Lahav (2005): "Threat, anxiety and support of antiterrorism policies", *American Journal of Political Science* 49 (3): 593-608

[44] Jost, J.T., J. Glaser, A.W. Kruglanski, F.J. Sulloway (2003): "Political conservatism as motivated social cognition", *Psychological Bulletin* 129(3), 339-375

[45] Jusot, F., S. Tubeuf and A. Trannoy (2013): "Effort or circumstances: how important is their correlation for inequality of opportunity in health?", *Health Economics*, 22(12): 1470–1495

[46] Kahneman, D. and Krueger, A.B. (2006): "Developments in the Measurement of Subjective Well-Being", *Journal of Economic Perspectives*, 22, 3-24

[47] Kamstra, M., L. Kramer and M. Levi (2003): "Winter Blues: A SAD Stock Market Cycle", *American Economic Review*, , 93(1), 324-343

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

[49] Krueger, A. (2007), *What Makes a Terrorist? Economics and the Roots of Terrorism*, Princeton University Press

[50] Krueger A.B. and Schkade, D.A. (2008): "The reliability of subjective well-being measures", *Journal of Public Economics*, 92: 1833.1845

[51] LaFree, G. and L. Dugan (2007): "Introducing the Global Terrorism Database", *Terrorism and Political Violence*, 19, 181-204.

[52] Lerner, J.S., R.M. Gonzalez, D.A. Small and B. Fischoff (2003): "Effects of Fear and Anger on Perceived Risks of Terrorism", *Psychological Science* 14 (2): 144–50

[53] Levinson, A. (2012): "Valuing public goods using happiness data: The case of air quality", *Journal of Public Economics*, 96(9), 869-880

[54] Liberini, F. M. Redoano and E. Proto (2017): "Happy voters", *Journal of Public Economics*, 146, 41-57

[55] Luttmer, E. (2005): "Neighbors as negatives: relative earnings and well-being", *Quarterly Journal of Economics* 120 (3), 963–1002

[56] Metcalfe, R., N. Powdthavee, and P. Dolan (2011): "Destruction and Distress: Using a Quasi-Experiment to Show the Effects of the September 11 Attacks on Mental Well-Being in the United Kingdom", *Economic Journal* 121 (550), F81–F103

[57] Montalvo, J. G. (2011): "Voting After the Bombings: A Natural Experiment on the Effect of Terrorist Attacks on Democratic Elections", *Review of Economics and Statistics* 93(4), 1146-1154

[58] Nail, P.R., McGregor, I., Drinkwater, A.E., Steele, G.M., Thompson, A.W. (2009): "Threat causes liberals to think like conservatives", *Journal of Experimental Social Psychology* 45 (4), 901–907

[59] Olken, B.A. (2009): "Do Television and Radio Destroy Social Capital? Evidence from Indonesian Villages", *American Economic Journal: Applied Economics*, 1(4), 1-33

[60] Oswald, A., & Wu, S. (2010): "Objective confirmation of subjective measures of human well-being: Evidence from the USA", *Science*, 327, 576-579

[61] Panagopoulos, C. (2006): "The polls-trends: Arab and Muslim Americans and Islam in the aftermath of 9/11", *Public Opinion Quarterly* 70(4):608–624

[62] Pape, R. (2003): "The Strategic Logic of Suicide Terrorism", *American Political Science Review* 97(03), 343-361

[63] Powdthavee, N. (2015): "Would you like to know what makes people happy? An overview of the data sets on subjective well-being", *Australian Economic Review*, 48, 3, 314–320

[64] Rehman, F.U. and P.Vanin (2017): "Terrorism risk and democratic preferences in Pakistan", *Journal of Development Economics* 124, 95–106

[65] Rohner, D. and B.S. Frey (2007): "Blood and ink! The common-interest-game between terrorists and the media", *Public Choice*, 133 (1–2), 129–145.

[66] Romanov, D., A. Zussman, and N. Zussman (2012): "Does Terrorism Demoralize? Evidence from Israel", *Economica* 79, 313, 183–98.

[67] Rubin, G.J., Brewin, C.R., Greenberg, N., Simpson, J. and Wessely, S. (2005): "Psychological and behavioural reactions to the bombings in London on 7 July 2005: cross sectional survey of a representative sample of Londoners", *British Medical Journal*, 331: 606

[68] Salguero, J.M., A. Cano-Vindel, I. Iruarrizaga, P. Fernández-Berrocal, S. Galea (2011): "Trajectory and Predictors of Depression in a 12-Month Prospective Study after the Madrid March 11 Terrorist Attacks", *Journal of Psychiatric Research* 45(10), 1395–403.

[69] Schüller, S. (2015): "The 9/11 Conservative Shift", *Economics Letters* 135, 80–84

[70] Senik, C. (2004): "When Information Dominates Comparison: Learning From Russian Subjective Panel Data", *Journal of Public Economics*, 88, 2099-2123

[71] Senik, C. (2005): "Income distribution and well-being: what can we learn from subjective data?", *Journal of Economic Survey*, 19(1), 43–63

[72] Silver, R.C., Holman, A., McIntosh, D.N., Poulin, M., Gil-Rivas, V. (2002): " Nationwide Longitudinal Study of Psychological Responses to September 11", *Journal of the American Medical Association*, 288: 1235-1244

[73] Spolaore, E. & R. Wacziarg (2016), "Ancestry and development: New evidence", mimeo

[74] Straetmans, S., Verschoor, W.F.C. and Wolff, C. (2008): "Extreme US Stock Market Fluctuation in the Wake of 9/11", *Journal of Applied Econometrics*, 23: 17-42

[75] Stutzer, A. (2004): "The role of income aspirations in individual happiness", *Journal of Economic Behavior & Organization*, 54(1), 89-109

[76] Sunstein, C.R., 2003. Terrorism and probability neglect. Journal of Risk and Uncertainty 26, 121–136

[77] Valiño, A., M. Buesa, and T. Baumert (2010): "The economics of terrorism: an overview of theory and applied studies", in M. Buesa and T. Baumert (Eds.), *The Economic Repercussions of Terrorism*. Oxford, UK: Oxford University Press, 3-35

[78] Weimann, G. (2005): "The Theater of Terror", *Journal of Aggression, Maltreatment & Trauma*, 9:3-4, 379-390

A Appendix A: Data and Statistics

A.1 Harmonizing Panel Datasets

Harmonizing Well-Being Measures. The life-satisfaction question is relatively comparable across the different datasets at use. In the GSOEP, SHP and HILDA, the question is framed as: "How satisfied are you with your life as a whole, all things considered?". In the BHPS: "How dissatisfied or satisfied are you with your life overall?". In the RMLS: "To what extend are you satisfied with your life in general at the present time”". In the PSID: "Please think about your life-as-a-whole. How satisfied are you with it?". The answer is reported on different scales: 5 points in the RMLS and PSID, 7 in the BHPS and 11 in the other countries. In ascending order of satisfaction, answers are scaled as follows: from 0 ("not at all satisfied") to 4 ("fully satisfied") in the RMLS, from 5 ("not at all satisfied") to 1 ("completely satisfied") in the PSID, from 1 ("completely dissatisfied") to 7 ("completely satisfied") in the BHPS, from 0 ("completely dissatisfied") to 10 ("completely satisfied") in the GSOEP, SHP and HILDA. Hence, it is necessary to harmonize the scales across datasets.

Since a majority of countries have an 11-point scale, our baseline approach consists in expanding the life-satisfaction answers in the PSID, the RLMS and the BHPS to 11 points. For each individual in the PSID and RLMS, we draw a random discrete number in the intervals [0-2], [3-4], [5-6], [7-8], [9-10] for ordinal values 1 to 5 respectively (and similarly in 7 intervals in the BHPS). The best approach consists in bootstrapping estimations over a large number of such draws. Yet, this gave indifferentiable results compare to a single draw, which we use for most of our analysis. We have also tried different reasonable assignments rules for the definition of segments, again without much difference with baseline results. Results with bootstrapped estimations and alternative definitions are available from the authors.

An alternative approach, presented in our sensitivity checks, involves collapsing answers to the least common denominator, i.e. the 5-point scale used in the RMLS and the PSID.[37] The mean level of SWB for each country is reported in Table A.1, in their original scale (first row), in the 0-10 harmonized scale (second row) and in the 1-5 harmonized scale (third row). The country ordering based on mean values is consistent across scales, with the highest score in Switzerland and the lowest in Russia.

Common Determinants of Well-Being. We aim to warrant the comparability of control variables across samples. Some determinants of SWB are readily comparable across countries and over time (e.g., age, gender, marital status, family size). We detail here the treatment of key variables in well-being regression, namely income, employment, health status and education

[37] That is, we assign values 1 to 5 to the intervals [0-2], [3-4], [5-6], [7-8] and [9-10] respectively, in the GSOEP, SHP and HILDA, and to intervals [0-1], [2-3], [4-4], [5-5], [6-7] respectively, in the BHPS.

(see Clark et al., 2008, Senik, 2005). Income is defined in all surveys as the sum of all income sources in the household after governmental transfers. We simply convert household income into 2011 USD (using World Bank indicators). The employment status is a dummy variable which indicates whether people are currently employed. The most common definition of health is the self-assessed health variable, rescaled in an ascending order, i.e. from very poor (1) to very good (5).[38] We control for the number of years of schooling, as provided for in the GSOEP, SHP, HILDA and PSID; we had to reconstruct this variable for the UK and Russia using the highest education level achieved and information about education systems.

Table A.1: Descriptive Statistics

	Germany	United Kingdom	Switzerland	Russia Federation	Australia	USA	All Countries
	GSOEP (1994-2013)	BHPS (1996-2018)	SHP (1999-2013)	RLMS (2000-2013)	HILDA (2000-2013)	PSID (2009-2013)	
Life satisfaction: country-specific scale (a)	7.00	5.17	8.00	3.01	7.90	3.77	6.01
	(1.754)	(1.260)	(1.347)	(1.124)	(1.440)	(0.867)	(2.285)
Life satisfaction: 0-10 harmonized scale (b)	7.00	8.06	8.00	5.48	7.90	7.03	7.11
	(1.754)	(1.563)	(1.347)	(2.343)	(1.440)	(1.758)	(1.992)
Life satisfaction: 1-5 harmonized scale (c)	3.38	4.06	4.00	3.01	3.94	3.77	3.57
	(1.060)	(1.075)	(0.890)	(1.124)	(0.950)	(0.867)	(1.113)
Female (=1)	0.517	0.540	0.560	0.573	0.532	0.318	0.529
	(0.500)	(0.498)	(0.496)	(0.495)	(0.499)	(0.466)	(0.499)
Age	45.3	43.6	47.1	43.2	42.6	42.9	44.2
	(15.612)	(15.650)	(15.236)	(15.894)	(15.518)	(14.074)	(15.639)
Married (=1)	0.598	0.690	0.612	0.668	0.663	0.463	0.633
	(0.490)	(0.463)	(0.487)	(0.471)	(0.473)	(0.499)	(0.482)
Household size	2.8	2.9	2.9	3.3	2.9	2.9	2.9
	(1.231)	(1.328)	(1.392)	(1.486)	(1.442)	(1.555)	(1.361)
Household income (2011 USD) (d)	45,960	55,320	103,460	12,930	67,630	69,770	48,800
	(37,310)	(42,610)	(96,420)	(38,020)	(62,620)	(106,220)	(55,440)
Currently employed (=1)	0.621	0.659	0.730	0.632	0.705	0.718	0.651
	(0.485)	(0.474)	(0.444)	(0.482)	(0.456)	(0.450)	(0.477)
Health Status (5-point scale)	3.4	3.8	4.1	3.2	3.4	3.5	3.5
	(0.928)	(0.935)	(0.635)	(0.693)	(0.949)	(1.036)	(0.915)
#Observations (individual x time)	301,679	140,600	40,479	134,846	108,164	24,923	750,691

Source: Own calculations from GSOEP, BHPS, SHP, RLMS, HILDA and PSID. The samples retains individuals aged 18-75 years old and excludes first-generation migrants. Standard deviations are in parentheses.

(a) Measured on a 11-points scale in GSOEP, SHP and HILDA, a 7-point scale in the BHPS, a 5-point scale in PSID and RLMS.

(b) The scales are harmonized into a 11-point scale (0-10)

(c) The scales are harmonized into a 5-point scale (1-5)

(d) Household income is converted into USD using yearly average exchange rates.

[38] Self-assessed health is widely used in health economics, and despite being subjective, it has been shown to predict disability, chronic diseases and health care utilization (Jusot et al., 2013).

A.2 Global Terror Data and Time Matching

Table A.2: Portrait of Terror: Breakdown of Fatalities and Incidences (1994-2013)

	Total # events	Daily mean # incidences (excluding zeros)	Daily mean # fatalities (excluding zeros)	Attack Characteristics: Breakdown							
				Explosion-bombing		Suicide bombing		Longer than 24 hours		Multiple attacks	
				incidences (%)	fatalities (%)	incidences (%)	fatalities (%)	incidences (%)	fatalities (%)	incidences (%)	fatalities (%)
All Terror Events	70,118	18.51	36.12	0.51	0.46	0.04	0.20	0.05	0.05	0.13	0.14
		(13.38)	(52.90)	(0.50)	(0.50)	(0.20)	(0.40)	(0.21)	(0.21)	(0.34)	(0.34)
<u>Daily Mean Terror by Years</u>											
1994	3,455	12.41	27.33	0.33	0.16	0.00	0.03	0.03	0.02	0.09	0.01
		(6.62)	(87.52)	(0.47)	(0.37)	(0.06)	(0.17)	(0.17)	(0.14)	(0.28)	(0.11)
1995	3,079	14.31	20.01	0.26	0.28	0.01	0.05	0.03	0.04	0.11	0.04
		(13.44)	(26.43)	(0.44)	(0.45)	(0.08)	(0.21)	(0.16)	(0.21)	(0.31)	(0.20)
2000	1,777	7.86	16.30	0.50	0.30	0.02	0.07	0.08	0.12	0.20	0.07
		(6.53)	(19.76)	(0.50)	(0.46)	(0.14)	(0.25)	(0.27)	(0.32)	(0.40)	(0.26)
2005	2,010	7.92	22.75	0.53	0.62	0.10	0.37	0.05	0.03	0.12	0.11
		(4.17)	(23.63)	(0.50)	(0.49)	(0.30)	(0.48)	(0.22)	(0.18)	(0.32)	(0.32)
2010	4,782	16.09	23.65	0.52	0.56	0.04	0.30	0.06	0.05	0.12	0.12
		(9.11)	(22.99)	(0.50)	(0.50)	(0.19)	(0.46)	(0.25)	(0.22)	(0.32)	(0.33)
2013	11,952	36.35	65.34	0.56	0.55	0.05	0.20	0.05	0.05	0.19	0.21
		(12.15)	(37.52)	(0.50)	(0.50)	(0.22)	(0.40)	(0.21)	(0.22)	(0.40)	(0.41)
<u>Daily Mean Terror by World Regions</u>											
North and Central America	1,561	11.47	30.72	0.25	0.06	0.01	0.69	0.04	0.01	0.16	0.71
		(8.94)	(154.83)	(0.43)	(0.24)	(0.08)	(0.46)	(0.19)	(0.08)	(0.36)	(0.45)
South America	3,835	13.35	29.79	0.43	0.25	0.00	0.01	0.11	0.11	0.18	0.18
		(9.78)	(47.40)	(0.50)	(0.43)	(0.04)	(0.12)	(0.31)	(0.32)	(0.38)	(0.38)
East/Southeast Asia & Oceania	6,537	19.01	34.24	0.40	0.29	0.01	0.04	0.04	0.06	0.18	0.12
		(14.04	(40.21)	(0.49)	(0.45)	(0.07)	(0.20)	(0.20)	(0.24)	(0.39)	(0.33)
South and Central Asia	23,679	19.78	36.06	0.51	0.49	0.05	0.21	0.05	0.04	0.11	0.07
		(13.21)	(35.89)	(0.50)	(0.50)	(0.22)	(0.41)	(0.23)	(0.19)	(0.31)	(0.26)
Western and Eastern Europe	4,910	13.87	24.24	0.59	0.46	0.00	0.07	0.01	0.01	0.21	0.30
		(12.53)	(47.62)	(0.49)	(0.50)	(0.06)	(0.25)	(0.10)	(0.09)	(0.40)	(0.46)
Russia and New Ind. Countries	2,314	14.25	30.07	0.54	0.51	0.03	0.17	0.03	0.18	0.08	0.17
		(10.46)	(78.09)	(0.50)	(0.50)	(0.18)	(0.38)	(0.18)	(0.39)	(0.26)	(0.37)
Middle East and North Africa	21,259	20.01	40.29	0.61	0.64	0.07	0.28	0.03	0.03	0.12	0.15
		(14.24)	(48.52)	(0.49)	(0.48)	(0.26)	(0.45)	(0.17)	(0.16)	(0.32)	(0.35)
Sub-Saharan Africa	6,023	18.26	41.11	0.29	0.17	0.02	0.04	0.10	0.08	0.16	0.12
		(12.13)	(73.26)	(0.46)	(0.38)	(0.14)	(0.19)	(0.30)	(0.27)	(0.37)	(0.33)

Notes: authors' calculations using the Global Terrorism Database 1994-2013. Fatalities represent the number of persons killed. Incidences are the counts of all terror events. Decomposition is given in % of all events, for instance: 51% of all events corresponds to explosion-bombing attacks. Standard deviations are in parentheses.

Figure A.1: The Geography of Terror

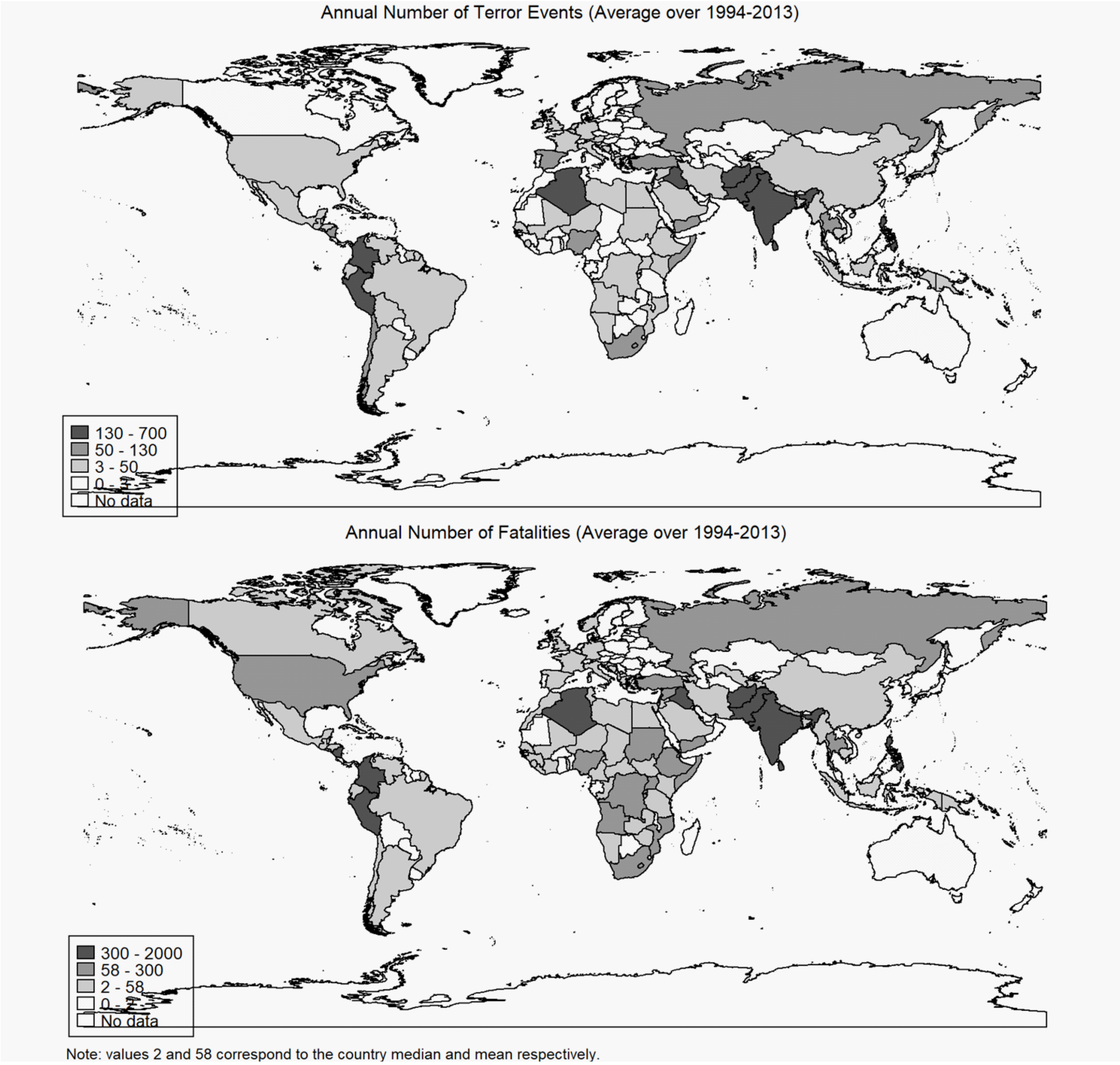
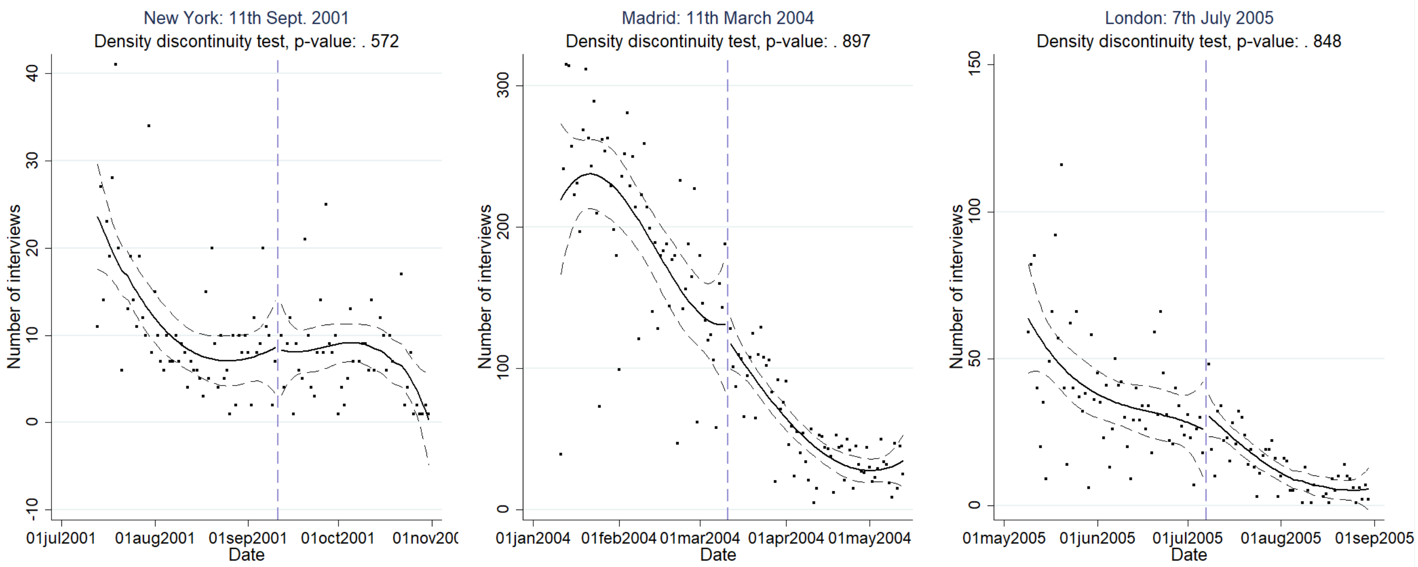


Table A.3: Distribution of Interviews and Terror Incidences by Months

	Distribution of terror events	Distribution of interviews						
			Germany	United Kingdom	Switzerland	Russian Federation	Australia	USA
	All Countries	All Countries	GSOEP (1994-2013)	BHPS (1996-2008)	SHP (1999-2013)	RLMS (2000-2013)	HILDA (2000-2013)	PSID (2009-2013)
January	.079	.057	.108	.037	.044	.018	.008	.000
February	.071	.131	.310	.022	.009	.009	.008	-
March	.081	.108	.249	.019	-	.007	.000	.121
April	.083	.062	.129	.013	-	-	-	.249
May	.090	.040	.076	.009	-	-	-	.234
June	.084	.024	.047	-	-	-	-	.165
July	.092	.017	.034	-	-	-	.003	.089
August	.090	.036	.020	-	.008	-	.176	.051
September	.078	.177	.013	.409	.326	.007	.517	.028
October	.088	.214	.009	.315	.384	.546	.210	.023
November	.088	.105	.003	.137	.176	.324	.066	.022
December	.077	.029	.001	.040	.054	.089	.012	.018

Notes: authors' calculations using the Global Terrorism Database and the panel datasets as indicated. The figures are calculated by averaging over all waves of the panels.

Figure A.2: Daily Distribution of Interviews around Salient Events (GSOEP)



B Appendix B: Sensitivity Analysis and Additional Results

B.1 Alternative Controls

In Table B.1, we compare the baseline (column 1) to alternative specifications in terms of controls. We raise a specific point about our fatality measure: it might capture the specific form of terror, for instance the shock of a bombing attack, rather than the death toll associated with it. This apparent omitted variable can actually be controlled for with the inclusion of vector C_{td-1}. This vector comprises dummies for attack specificities (multiple attacks, extended attack, suicide attack), attack types (explosion/bombing, armed assault, assassination, etc.), the three criteria defining terror (intentionality, intention to coerce/intimidate/publicize to a large audience, standing outside international humanitarian law), and 13 broad world regions where terror took place (as summarized in Table A.2). We cannot include the characteristics of all previous-day events but focus on those of the largest event (defined by the total number of killed and wounded). In this way, we capture the visibility of this event and more qualitative forms of intensity about the previous day terror (like the shock from suicide bombing or from particularly long attacks). Table B.1 first check the sensitivity of our results to the exclusion of these characteristics C_{td-1} (column 2). These characteristics are not correlated with the number of events, and indeed the coefficient hardly changes. They relate slightly more to the number of fatalities insofar as the main event has been responsible for most of the human losses of that day (as captured in the type of attack, for instance explosion/bombing). Still, coefficients on the number of fatalities are not affected. These results indicate that our main measures of terror intensity capture well the world climate of terror – and not the specificities of a large and possibly highly mediatized event.[39]

Then, we compare our baseline to estimations including additional information about terror events. Column 3 includes the full set of country dummies for places where past-day terror took place. It is expected to bring some collinearity with the terror incidences variable especially. Arguably, the fact that an attack took place in Iraq rather than in Germany necessarily brings additional information rather than the mere count of terror events. Nonetheless, we want to know whether adding this information affects our terror intensity measures. Formally, if the model includes binary effects for J countries, $\sum_j \delta_j 1(country_j = 1)$, then terror incidences is written $T_{td-1} = \sum_j 1(country_j = 1)$ if there is no multiple events in a country on a given day. This is equivalent to replacing βT_{td-1} by $\sum_j (\delta_j + \beta) 1(country_j = 1)$: β represents the average effect of world terror and δ_j capture country-specific deviation to it. This explains why terror effects are relatively similar to the baseline in this case (column 3). While C_{td-1} contains

[39] Note that the R-squared of a regression of fatalities on C_{td-1} is only .12.

only the identity of the world region where the main event took place, country effects carry interesting information since terror in specific countries may have more or less repercussions on individual welfare.

We pursue the sensitivity check by controlling for measures of the proximity to terror (in the text, proximity measures are used for heterogeneous effects). Column 4 includes the log average physical distance to previous day terror events while column 5 includes the log average genetic distance between the individual (based on his/her country) and countries where previous-day terror took place.[40] In both cases, our effects are relatively similar to the baseline.[41]

B.2 Varying Estimation Methods

In Table B.2, we compare estimations methods. Column 1 reports baseline results using fixed effects estimations. Column 2 shows estimates from a model using Mundlak's quasi-fixed effects (QFE). This approach combines both between and within variation. The individual effect is based on a slightly more structural specification where $\varphi_i = Z_i + \overline{W_{it}} + u_i$ includes time-invariant variables Z_i that are otherwise captured by fixed effects (gender, country, cohort, etc.), within-means of relevant time-variant variables $\overline{W_{it}}$ (household income, household size, age and health) and a normally-distributed random effect u_i. The results do not show particular deviation from the baseline estimates. In column 3, we report estimates based on a discrete model. We acknowledge the ordinal nature of the dependent variable and allow for unobserved individual effects in this nonlinear context by using the "Blow-Up and Cluster" fixed effects ordered logit (see Baetschmann et al., 2015). The coefficients are still very significant for both incidences and fatalities. They are around twice larger (these are not marginal effects) and so are the coefficients on log income, so that equivalent income effects are very much in line with basic results. Finally, column 4 points to smaller but still significant effects when ignoring individual effects in pooled linear regressions. Overall, our conclusions are not dramatically

[40] For each respondent, we use the *centroids* (central latitude and longitude) of the smallest geographical area in the sample (ex: German county or "Raumordnungsregionen", US states, etc.). For genetics, we rely on the database on genetic distances among various world populations collected by Spolaore and Wacziarg (2016). For both physical and genetic distances, we have run alternative estimations using distance to the largest event (with respect to the number of fatalities) rather than the mean distance to all events. Results, available from the authors, are highly similar.

[41] We also notice that our average treatment effect is based on a measure that gives equal weights to all terror incidents of the previous day, irrespective of their distance to the respondents' location. To calculate a distance-weighted sum of total number of fatalities, we denote $\{f_{1,d}, ..., f_{n_d,d}\}$ the vector of fatality counts on day d and for event $i = 1, ..., n_d$ and $\Lambda = \{\lambda_{1,d}, ..., \lambda_{n_d,d}\}$ the vector of distances to each event of day d using events' geographical coordinates. Rather than a fatality count $\sum_{i=1}^{n_d} f_{i,d}$, we can calculate a closeness-weighted sum of fatalities $\sum_{i=1}^{n_d}(1 - \frac{\lambda_{i,d}}{\max(\Lambda_d)})f_{i,d}$. In this case, the effect is again very similar to the baseline and highly statistically significant.

Table B.1: Welfare Impact of Global Terror: Sensitivity to Terror Location Controls

	(1): baseline	(2)	(3)	(4)	(5)
# Incidences (log)	-0.0148 ***	-0.0155 ***	-0.0155 ***	-0.0153 ***	-0.0125 ***
	(0.0026)	(0.0025)	(0.0032)	(0.0037)	(0.0036)
Equivalent Income	-0.174	-0.182	-0.182	-0.180	-0.147
# Fatalities (log)	-0.0076 ***	-0.0072 ***	-0.0080 ***	-0.0083 ***	-0.0066 ***
	(0.0014)	(0.0013)	(0.0018)	(0.0020)	(0.0020)
Equivalent Income	-0.090	-0.085	-0.094	-0.098	-0.078
R-Squared	0.077	0.077	0.077	0.077	0.077
#Observations	750,691	750,691	750,691	705,649	647,102
Individual Effect	FE	FE	FE	FE	FE
Terror characteristics	NO	YES	YES	YES	YES
Countries of terror dummies	NO	NO	YES	NO	NO
Average physical distance	NO	NO	NO	YES	NO
Average genetic distance	NO	NO	NO	NO	YES

Linear estimations of life satisfaction on incidences (# or dummy) or fatalities (# or dummy). Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Sensitivity: (1) is our baseline, (2) includes the terror characteristics of the past-day main event comprising attack specificities (multiple attacks, extended attack, suicide attack), attack types (armed assault, assassination, explosion/bombing, etc.), the 3 terrorism definition critieria, and 13 broad world regions, (3) additionally controls for dummies of countries where all terror events took place, (4) controls for the average distance to these countries, (4) controls for the average genetic distance to these countries. Clustered standard errors are presented in parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.

affected by (the way we account for) individual heterogeneity, which confirms the robustness of an identification strategy based on cross-sectional variation in interview days around terror events of different intensities.

Table B.2: Welfare Impact of Global Terror: Sensitivity to Estimation Methods

	(1): baseline	(2)	(3)	(4)
# Incidences (log)	-0.0148 ***	-0.0151 ***	-0.0278 ***	-0.0130 ***
	(0.0026)	(0.0025)	(0.0052)	(0.0030)
Log(Household Income)	0.0849 ***	0.0997 ***	0.1741 ***	0.1259 ***
	(0.0029)	(0.0028)	(0.0066)	(0.0028)
Equivalent Income	-0.174	-0.151	-0.160	-0.103
# Fatalities (log)	-0.0076 ***	-0.0078 ***	-0.0148 ***	-0.0076 ***
	(0.0014)	(0.0013)	(0.0028)	(0.0016)
Log(Household Income)	0.0848 ***	0.0996 ***	0.1740 ***	0.1258 ***
	(0.0029)	(0.0028)	(0.0066)	(0.0028)
Equivalent Income	-0.090	-0.078	-0.085	-0.060
R-Squared	0.077	0.671	0.043	0.672
#Observations	750,691	750,691	750,691	750,691
Individual Effect	FE	QFE	FE	none
Estimation Method	linear	linear	ologit	linear

Estimations of life satisfaction on incidences (# or dummy) or fatalities (# or dummy). Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence). Individual effects are modelled as: (1) fixed effects (FE), (2) Mundlak's quasi-fixed effects (QFE), which include country fixed effects and the mean value over time for key variables (income, education, household size, health and age) plus a random effect. All estimations are linear except in (3), which uses an ordered logit "blow and cluster" approach with FE. Clustered standard errors are presented in the parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.

B.3 Alternative Terror/SWB Measures

Table B.3 first reports the baseline, which relies on the log of incidence/fatality counts (Column 1). Column 2 shows marginal effects obtained when incidences and fatalities are introduced jointly in the model. Note that the correlation between incidences and fatalities is relatively high (.59) if we exclude the top-5 events, which account for more than 400 fatalities. When including those, the correlation is more modest (.23). As expected, estimates for both measures become smaller when added jointly: two-thirds of the baseline for incidences and half for fatalities. They are nonetheless still significant, at 5% and 10% respectively. Column 3 adopts the specification of Frey et al. (2009) whereby incidences and fatalities are included in a linear (rather than log) specification. In equivalent terms, we obtain larger effects, especially for incidences. Yet they are not statistically different from the baseline.[42] Column 4 reports estimates where terror intensity is replaced by dummy variables, i.e. whether terror events occurred or whether people got killed the previous day. As discussed, such an extensive margin does not provide much variation (only 3.7% of the 7,305 days are exempt from terror incidents), so that the insignificant effect for incidence is not surprising. There is a little more extensive-margin variation with respect to fatalities, which may explain that we obtain a significant effect in this case. Anyhow, it is expected that the mere occurrence of an event somewhere in the world has little impact – we have rather embraced the variation in global terror intensity. Finally, in column 5, we check the sensitivity of our results to the way in which we harmonize SWB scales across countries. With the 5-point scale, coefficients are necessarily smaller in magnitude – and actually not far from half of the coefficients obtained with the 11-point scale.

Table B.3: Welfare Impact of Global Terror: Additional Sensitivity Checks

	log(#incidence+1) or log(#fatalities+1) : baseline	log (#incidence+1) and log(#fatalities+1) simultaneously in the same regression	#incidence or # fatalities (linear rather than log)	Dummies for Terror Events or Fatalities	SWB harmonized on a 5-point scale
Incidences	-0.0148 ***	-0.0096 **	-0.2133 ***	-0.0069	-0.0082 ***
	(0.0026)	(0.0039)	(0.0408)	(0.0097)	(0.0018)
Equivalent Income	-0.17	-0.11	-0.26	-0.08	-0.12
Fatalities	-0.0076 ***	-0.0038 *	-0.0071 ***	-0.0154 ***	-0.0043 ***
	(0.0014)	(0.0021)	(0.0018)	(0.0051)	(0.0010)
Equivalent Income	-0.09	-0.04	-0.11	-0.13	-0.06
R-Squared	0.077	0.080	0.080	0.072	0.210
#Obs.	750,691	750,691	750,691	750,691	750,691

Linear estimations of life satisfaction on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Clustered standard errors are presented in the parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.

B.4 Sensitivity to Timing.

Time matching is a difficult exercise given that multiple terror events can occur on a given day, they can last several hours and the exact timing is generally unknown. Our baseline has focused on previous-day events for clarity. Terror events that take place on the interview day may also matter, insofar as they occurred prior to the interview. We have mentioned in the main text that the past-day assumption may slightly underestimate the treatment effect if, among the control group, some people are observed on the event day and already affected by the event. The same-day assumption also carries some fuzziness since individuals observed on the event

[42] The 95% confidence interval for our incidences equivalent income effect is $[-.29, -.13]$ in the baseline log specification and $[-.36, -.16]$ with a linear form of terror incidence.

day but before the event happens are not yet treated. Table B.4 compares our baseline for incidences and fatalities (column 1) with the alternative matching of interviews with same-day events (column 2). The effect is smaller in this case but still significant. We finally test the effect from terror events occurring either on the interview day or the previous day (column 3). The results show a larger depressing impact using incidences – yet not significantly larger compared to the baseline – since SWB is potentially impacted by more events. For fatalities, the point estimate coincides with the baseline. We have also run placebo estimations using events occurring the next day, which consistently lead to a zero effect (unreported).

Table B.4: Welfare Impact of Global Terror: Timing

Terror on:	Day before interview : baseline	Interview Day	Interview day and previous day
# Incidences (log)	-0.0148 ***	-0.0079 ***	-0.0172 ***
	(0.0026)	(0.0026)	(0.0030)
Equivalent Income	0.17	0.09	0.20
# Fatalities (log)	-0.0076 ***	-0.0036 ***	-0.0077 ***
	(0.0014)	(0.0014)	(0.0017)
Equivalent Income	0.09	0.04	0.09
R-Squared	0.077	0.071	0.081
#Obs.	750,691	750,691	750,691

Linear estimations of life satisfaction on incidences or fatalities. Models control for individual characteristics (age, education, marital status, health indicator, household size, # of children, log household income, year, month, country specific region of residence) and individual fixed effects. Clustered standard errors are presented in parentheses. *, **, *** indicates significance level at 10%, 5% and 1% levels respectively.