The Impact of Terrorism on Individual Well-being: Evidence from the Boston Marathon Bombing

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Abstract

A growing literature has concluded that terrorism affects the economy, yet less is known about its impact on individual welfare. This paper estimates the impact of the 2013 Boston Marathon Bombing on well-being, exploiting representative daily data from the American Time Use Survey and Well-Being Supplement. Using a combined regression discontinuity and differences-in-differences design, with the 2012 Boston marathon as a counterfactual, we find an immediate reduction in well-being of half a standard deviation. In particular, happiness declined sharply and stress rose significantly. While the effects do not persist beyond one week, they may entail adverse health and economic consequences.

Keywords: Well-being, Terrorism, Regression Discontinuity Design, Differences-in-Differences.

JEL classification: I31, J21, J22, F52.

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The increasing frequency and severity of terrorism has led many OECD governments to devote large budgets to terrorism prevention (Mueller and Stewart, 2014). The economic consequences of terrorist acts on aggregate measures of national output, financial markets, foreign direct investment, and tourism have been well documented (Enders *et al.*, 1992; Eckstein and Tsiddon, 2004; Gordon *et al.,* 2007; Abadie and Gardeazabal, 2008; Straetmans *et al.*, 2008). However, less is known about the economic costs of terrorism at the individual level.

Terrorism may affect individuals by increasing feelings of uncertainty, fear, and risk aversion (Becker and Rubinstein, 2011), which are widely known to affect economic behavior. Exposure to terrorism may lead to fear conditioning, in which repeated exposure to terrorist acts, for example through the media, may activate fear circuitry in the brain thus exacerbating negative emotions (Marshall *et al.,* 2007; Holman *et al.,* 2014) and affecting economic behavior. This is in line with evidence from Israel showing that media coverage largely contributes to the impact of fatal attacks on consumer behavior (Becker and Rubinstein, 2011). Brodeur (2018) also finds that terrorist attacks increase consumer pessimism regarding personal finances, business conditions, and buying conditions. Thus, with large-scale media coverage of terrorism, the well-being of individuals not directly involved in the attacks is likely to be affected. For example, there is evidence that media exposure to terrorist attacks, including the 9/11 attack in New York (Schlenger *et al.,* 2002) and the Oklahoma City bombing (Pfefferbaum *et al.,* 2001), is associated with trauma-related symptoms at the national level throughout the US. Terrorism may also increase feelings of stress, with spillovers on both adult and child health (Camacho, 2008; Pesko, 2014; Pesko and Baum, 2016; Black *et al.,* 2016; Cawley *et al.,* 2017) and economic decision making (Delaney *et. al.,* 2014).

In this paper we exploit repeated cross-sectional data from the American Time Use Survey (ATUS) and Well-Being (WB) module, collected on a daily basis for a representative random sample of the American population, to estimate the impact of the 2013 Boston marathon bombing on experienced well-being, encompassing feelings of happiness, stress, and other emotions associated with everyday life. This is the first study to estimate the impact of the Boston attack on individual well-being.[2]

Terrorist attacks, such as this one, may not always occur on random days as attacks are often timed close to political elections (Montalvo, 2011), as a reaction to violence from the

[2] The association between the Boston marathon bombing and adult and child stress has been examined in the psychological literature (e.g. Comer *et al.,* 2014).

‘other side’ (Jaeger and Paserman, 2008), or due to specific trade relations (Mirza and Verdier, 2008). As terrorism may affect those who live far from the actual place of the attack (e.g., Metcalfe *et al.,* 2011), identifying a ‘synthetic’ counterfactual as in Abadie and Gardeazabal (2003) who constructed a synthetic control group for the Basque region of Spain using other Spanish regions to estimate the effect of terrorism on GDP, may not always be a valid empirical approach. In addition, terrorists often plan their actions in order to obtain large media coverage, as in the case of the 2013 Boston marathon or the 2016 Bastille Day attack in Nice. As individual economic behavior and well-being may differ on such ‘special’ days, we argue that this non-random timing of terrorist attacks needs to be taken into account when measuring the individual-level impact of terrorism. To control for the potential non-randomness of terrorist attacks and that large sporting events may generate strong emotional reactions (e.g. Kavetsos and Szymanski, 2010; Card and Dahl, 2011) we take a combined regression discontinuity design (RDD) and differences-in-differences approach, by exploiting individual well-being responses reported around the 2012 Boston marathon, when there was no bombing, as an additional counterfactual. This is the first study to use such an approach to estimate the impact of terrorism; our contribution is therefore also methodological.

The economic literature on the individual well-being effects of terrorism (e.g. Frey *et al.,* 2007; Frey *et al.,* 2009; Krueger, 2007; Metcalfe *et al.,* 2011; Romanov *et al.,* 2012) typically uses subjective well-being questions to measure individual utility (Di Tella and MacCulloch, 2006; Clark, 2011). For example, Metcalfe *et al.* (2011) use a differences-in-differences approach with respondent fixed effects to compare the mental distress[3] of respondents from the British Household Panel Survey interviewed in the months before and after the 9/11 attacks. Tsai and Venkataramani (2015) adopt a similar approach, also for the 9/11 attacks, using subjective well-being information from the US Behavioural Risk Factor Surveillance System (BRFSS) on the number of days in the last month spent in poor mental health. Pesko (2014) also uses the BRFSS data to examine the impact of the Oklahoma City bombing on stress and smoking via an RDD, and Pesko and Baum (2016) take the temporal distance from the 9/11 attacks as an instrument for stress. Two studies, both using cross-sectional data from the National Longitudinal Study of Adolescent Health and the National Employee Survey, examine the impact of the 9/11 attacks on mental health using an RDD

[3] Mental distress is measured using 12 items from the General Health Questionnaire where respondents are asked how they have been feeling over the last few weeks on different dimensions such as feeling of happiness and ability to concentrate.

(Ford *et al.,* 2003; Knudsen *et al.,* 2005).[4] In general, this emerging body of work concludes that terrorist attacks lead to a reduction in subjective well-being.

We add to this literature, not only from a methodological perspective, but also by using a more responsive measure of individual well-being. The ATUS data contain measures of daily activities (Stancanelli *et al.,* 2012; Hamermesh and Stancanelli, 2015) and the WB module (designed by Alan Krueger) contains measures of unique emotional responses experienced during the day of the interview. The WB module solicits well-being across five dimensions: happy, stress, sad, tiredness, and pain. Three of the activities reported in the daily time-use diary were randomly selected, and for each activity respondents were asked to report how they felt during the activity in terms of these five emotions (also asked in a randomized order). This is referred to as 'experienced' well-being, typically measured using the day reconstruction method (DRM). While questions about satisfaction 'in general' or over the past few weeks/months/year can be powerful indicators of respondents' overall well-being, they may be subject to recall and cognitive biases based on longer time periods and without a direct connection to daily life activities (Kahneman *et al.,* 2004; Kahneman and Krueger, 2006; Dolan and Kahneman, 2008; Krueger and Mueller, 2012; Stone *et al.*, 2018), and/or reflect expectations rather than actual life experiences (Schwartz, 1999). Experienced well-being measures may then be more suitable for analysing the immediate impact of a significant event (such as a terrorist act), as they directly capture emotional responses to the event in real time (Kahneman *et al.,* 2004). Using these measures we can provide a unique and fine-grained analysis of the well-being impact of terrorism.[5]

The Boston marathon bombing took place on Monday 15th April 2013 when two bombs were detonated near the finish line, causing the death of three spectators and a policeman, and injuring 264 spectators. The attack was perpetrated by two brothers from a Chechen background. It was the first major terrorist act in the US since the 9/11 attacks and, unlike previous terrorist acts that tended to target the business community, the Boston attack was on a sporting event with 23,413 runners and one million spectators, many of whom were families and children (Kerns *et al.,* 2014). The aftermath of the attack led to an extensive manhunt lasting four days and involved a 'shelter in place' for one million Bostonians, door-

[4] Mental health is measured using a modified version of the Center for Epidemiological Studies Depression Scale where respondents report the number of days feeling different emotional states e.g., sadness, trouble getting to sleep etc.

[5] Bryson and MacKerron (2018) use panel data from Northern Ireland - where there is a long history of terrorism that is normally carried out by nationals – to measure respondent's experienced well-being based on real-time responses to a random ding from mobile phones. They conclude that only deadly attacks within a 20 kilometre radius affect well-being, and then only for 3 days.

to-door searches by armed military and law-enforcement officers, and the shutdown of public transport, as well as shootings and a carjacking until the perpetrators were apprehended (Comer *et al,.* 2014). The Boston attack received intensive national and international media coverage and the event was on the New York Times front-page for eleven consecutive days. The Boston attack was also widely reported on social media, with one-quarter of Americans following the event, and the number of Twitter users following the Boston Police Department increasing from 54K to 264K worldwide (Buntain *et al.,* 2016). Holman *et al.* (2014) find, using a representative survey of the US population administered between 2-4 weeks after the attack, that repeated media exposure to the bombing was associated with higher stress across all US States (although they did not address the issue of causality). Another study, using a word-emotion association lexicon in the April 2013 Twitter feed (of 134,245,610 tweets), finds a significant increase in the use of the word 'fear' on April 19th, the last day of the manhunt (Buntain *et al.,* 2016), which suggests a heightened sense of fear more generally.

Our empirical approach relies on a RDD that sets the days elapsed before and after the Boston marathon bombing as the running variable, combined with a differences-in-differences approach, by exploiting individual well-being responses reported around the 2012 Boston marathon to generate an additional control group. We find that the bombing significantly affected individuals' experienced well-being: happiness fell by about half a standard deviation in the immediate aftermath of the attack and stress rose by about the same amount. Overall, 'negative affect', a summary of all negative emotions, increased significantly due to the bombing, and there was a reduction in net affect (the difference between the average of positive and negative emotions) by over half of a standard deviation. The impact of the attack appears to have mostly faded away one week after the bombing (based on our event study estimates), which is consistent with other studies of terrorist attacks (e.g., Krueger, 2007).

Although the effects are transitory, the consequences of the terrorist attack in terms of foregone welfare may be long-lasting if health outcomes and economic decisions are impacted – although we cannot establish this with the data at hand. There is however evidence that stress significantly affects economic decision making (Delaney *et. al.,* 2014) and has long-term adverse effects on later health, especially for those in-utero and new-borns (Camacho, 2008; Currie and Rossin-Slater, 2013; Black *et al.,* 2016; Cawley *et al.,* 2017). Moreover, continuous exposure to stress, particularly in childhood, can induce structural changes in neural connectivity and have long-term consequences on brain functioning leading to later mental and physical disorders (Shonkoff *et al*., 2012) and poorer labor market outcomes (Knudsen *et al.,* 2006).

The remainder of the paper is structured as follows. Section 1 sets out the data and Section 2 presents the empirical approach. Section 3 then provides descriptive statistics and graphical evidence, while the estimation results are given in Section 4. Finally, the findings are discussed and conclusions are drawn in Section 5.

1. The Data, Sample Selection, and Outcome Variables

1.1.Data

The data come from the 2012 and 2013 American Time Use Survey (ATUS) and Well-Being module (WB), which is run by the Bureau of Labor Statics (BLS).[6] The ATUS respondents are a random sample of the American Current Population Survey (CPS) survey. The WB module is a supplementary survey which was included in the ATUS in order to gather information on respondents' emotional well-being. Therefore, the ATUS-WB is a cross-sectional survey with a representative sample of the US population including over eleven thousand randomly-selected respondents every year. The ATUS interviews take place on all days of the week, Monday to Sunday, in order to provide a representative picture of daily life, beginning in the January of each year and ending in December. The day of the interview is chosen by the BLS interviewers. Participants to the ATUS survey fill in a diary recording the activities carried out over the past 24 hours, starting in the middle of the night.[7] In the WB module, three of the activities reported in the time-use diary are then randomly drawn and respondents are asked to report the emotions they experienced during each of those three activities. In particular, five emotions are asked, in a randomized order, for each of the activities. This procedure to collect individual well-being data is known as the day reconstruction method and is well-established in the literature.

The response rate to the ATUS-WB survey is typically between 52 to 58 percent (depending on the year) and the BLS provides weights to correct for non-responses.[8] We account for these weights in all of our analyses.

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[6] The WB supplement was collected in 2010, 2012, and 2013 and was previously used to study the relationship between well-being and unemployment (Krueger and Mueller, 2012), income (Kushlev *et al.,* 2015), health (Schneider and Stone, 2014), family and work life (Flood and Genadek, 2016), and tiredness (Dolan and Kudrna, 2015).

[7] Activities have to be at least 5 minutes in duration to be included, which is a standard procedure in this literature.

[8] In addition, the WB weights account for the duration of each of the three activities for which respondents provided information about their emotions (see BLS (2014) and BLS (2015) for more information on this).

1.2 Outcome Variables

Appendix A provides the exact wording for the well-being questions taken from the WB module. Three activities were randomly-selected from those reported by the respondent in the daily diary[9] and respondents were asked to report their feelings for five different emotions associated with these activities: happy, sad, tiredness, pain and stress. The order in which these emotions were asked varied randomly across participants.[10] Each emotion was rated on a scale from zero (not having experienced any happiness at all, for example) to six (having experienced the greatest happiness possible). The reliability and validity of the experienced well-being questions in ATUS-WB has been established (see Lee *et al.,* 2016). We also conduct some additional tests reported in Appendix A. Non-responses and refusals are set equal to missing (there are very few of these compared to the many thousands of valid responses).

We examine feelings of happiness and stress, as these are the most relevant in terms of economic implications. Happiness is normally used as a subjective measure of individual welfare in the economics literature (Di Tella and MacCulloch, 2006); while stress has been largely studied in relation to health and other economic outcomes, as reviewed in the introduction. We also combine the negative emotions (sad, tiredness, pain and stress) to derive a measure of average negative affect – a frequently used measure in the experienced well-being literature (Doyle *et al.*, 2015). We also compute an overall measure of experienced well-being, so-called 'net affect', given by the difference between the happiness score and average negative affect score (Doyle *et al.*, 2015). We thus consider the following outcomes:

- Happy
- Stress
- Negative Affect (the average of sad, tiredness, pain and stress)
- Net Affect (the difference between happy and negative affect)

For each ATUS-WB survey respondent, we compute these four well-being measures for each of the three activities for which emotions were asked, and then take the average across the three activities.

[9] One issue with the WB module is that the way in which the activities were randomly-drawn changed in March 2013 (BLS, 2015), which is included in our period of analysis. Due to a programming error in the data-collection software, the last activity of the day (often sleep, grooming and personal activities) was excluded from being selected for the questions on experienced well-being until this error was detected and corrected on March 25, 2013. The survey weights were adjusted by the BLS to mitigate this error, and we use these weights in all analysis (including the graphs and descriptive tables). In addition, the data from the 2012 and 2013 surveys look very similar (see the t-tests in Table 1).

[10] Although the order was randomized across participants, for each participant the order in which the five emotional responses were asked for each of the three activities was the same.

To provide additional information on how individuals were affected by the bombing in terms of their time allocation, we also analyse the following activities drawn from the ATUS time use diary:

- Market hours
- Household work
- Child-care
- Active Leisure (exercising)
- Watching television or listening to the media
- Sleep

The economic literature on the impact of terrorism points to a significant and large negative effect on economic activity, for example entrepreneurs may move away from the place of continued attacks (Abadie and Gardazeabal, 2003). There is also evidence that security procedures increase in the aftermath of terrorist attacks and this may also, at least temporarily, reduce economic activity (Sandler and Enders, 2012). Feelings of fear experienced in the aftermath of terrorism may also temporarily reduce the time individuals spend outside the home (for example, Becker and Rubinstein (2011) find a drop in consumption at bars and use of buses). We may thus expect the Boston marathon bombing to reduce individual labor supply and active leisure activities (as exercising is often done outside) and potentially increase time spent watching television, listening to the media, and household work. If individuals wish to protect their children, time devoted to child-care may also rise. Last, hours of sleep may also fall, given evidence that post-traumatic stress disorder leads to less sleep and poorer sleep efficiency (Kim and Dimsdale, 2007).

1.3 Sample Selection and Size

The ATUS-WB survey includes over eleven thousand respondents each year. Our estimation sample includes respondents that answered the survey questions in the 35 days (our optimal bandwidth for RDD) before and after the Boston marathon (which was on Monday 16th April in 2012 and Monday 15th April in 2013) and excludes those that answered the survey on the exact day of the Boston marathon (which is normal practice in RDD studies, as only some respondents may be aware of the bombing at the time of the interview, which may confound the estimation results).[11] The following is worth noting:

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[11] Our results are robust to their inclusion, as we show in Table 2.

a) The total estimation sample is 4659 observations, of which 2354 pertain to 2013 and 2305 to 2012.
b) The daily average number of survey respondents who completed the survey during the estimation period (spanning 35 days before and 35 days after the 2012 and 2013 Boston marathon day) varies between 11 and 170 respondents per day in 2013; and between 6 and 130 per day in 2012.
c) Restricting the sample to those who live in States close to Boston (see definition below), the sample size falls to 372 observations in 2012 and 390 observations in 2013.
d) Including respondents who were interviewed on the exact day of the Boston marathon, increases the sample slightly, to 4716 observations (as 28 respondents filled in the survey on Monday 16th April in 2012 and 29 on Monday 15th April in 2013).

1.4 Other Variables

As the ATUS respondents are a random sample of the CPS, the ATUS-WB data were matched to the CPS data to obtain information on gender, age, education, economic status, family composition, race, State of residence, area of residence (metropolitan/urban versus rural), and total household income. Economic status is a categorical variable including the employed, unemployed, and economically inactive: we include a dummy for employment (including more detailed categorical variables for economic status does not affect our conclusions). We construct a race variable with categories including White, Black, and an Others group including Hispanics and other ethnic groups. We construct a series of education dummies for college drop-out, high school, and less than high school, with college education being the reference group. Total household income is measured in sixteen intervals. Setting the respondent's household income equal to the mid-bound of the household income interval to which the respondent's household income is assigned (out of the 16 intervals available)[12] produces a distribution of income with a median of $54,999, which is an overestimate of the 2013 median household income of $52,250 (according to Noss, 2014, for the US Census Bureau).[13] As the sample size becomes quite small when focusing on specific States for a short period of time around the day of the attack, we do not focus only on Massachusetts but

[12] For the top income interval (the 16th) which is open-ended, we take its lower bound.
[13] Alternatively, using the lower bound of each income bracket would produce an underestimated median household income figure of about $50,000.

define ‘States close by’ as the geographically-close States of Connecticut, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont, as well as Massachusetts.[14]

2. Empirical Method

Most of the empirical literature to date considers terrorism as an exogenous shock. However, terrorists often plan their attacks to occur on ‘special event days’, such as the 2013 Boston marathon bombing and the terrorist attack during the 2016 14th July Bastille Day celebrations in Nice, France. As individual outcomes may already be different on such days, even in the absence of any attack, we use survey responses around the days of the previous Boston marathon, in 2012, to produce a control group. To capture the immediate impact of the attack, we combine thid differences-in-differences model with a RDD, in which respondents who answered the survey in the days before the attack serve as an (additional) counterfactual to those who were interviewed after the attack.

2.1 Regression Discontinuity Design (RDD)

An RDD using the elapsed distance in days from the event in question as the running variable (such as, for example, the individual’s birthday or a new Law being passed) is an accepted procedure as long as this distance cannot be manipulated by the individual (Lee and Lemieux, 2010). In our context, this involves examining whether the ATUS-WB survey was run continuously over the period of the attack. This can be tested using the McCrary approach (McCrary, 2008). Figure B1 in Appendix B shows that the frequency of survey responses did not vary discontinuously at the cut-off (the 2013 Boston marathon). We also run the same test for the 2012 Boston marathon, and find similar results (also see Figure B). Next, we test that other control variables did not vary discontinuously at the cut-off, as this would invalidate the use of the RDD method. We thus plot the sample characteristics, such as household income, area of residence, and education (Figure B2) and gender, age, race, and number of children (Figure B3) in the days before and after the Boston bombing. None of these variables are discontinuous before or after the bombing, corroborating our methodological approach.

Under RDD, the impact of the bombing on the outcome *W* (here experienced well-being or time use) is captured by the ‘treatment’ *T*, which takes a value of one starting on the Boston marathon date (e.g. April 15th 2013) and thereafter, and equals zero in the days before

[14] If New York, Pennsylvania, and New Jersey are considered too far away to be in the ‘nearby’ group then we will underestimate the ‘close-by’ effect in specification 3c of Table 4.

the Boston marathon date. The running variable, *D*, is defined as the distance in days from the terrorist attack: this is negative before the attack, zero on the day of the attack, and positive thereafter.[15] The outcome variable *W* is observed either before the attack $W(_0)$ or after the attack $W(_1)$, but never at both times for the same individual – as we have cross-sectional data. It is assumed that any change in outcomes before and after the attack is due to the attack itself. This is a reasonable assumption as the sample is randomly drawn by the BLS and individuals were randomly allocated to answer the survey in the days before and after the attack as tested in Appendix B and discussed above; and also no other variable is found to vary discontinuously on the day of the attack. For each individual *i*, interviewed before or after *T*, exposure to the treatment *T* is thus a deterministic function of the calendar day on which the ATUS-WB survey was answered. We estimate the average (local) impact (γ) of the attack on individual well-being by taking the difference between the well-being of individuals interviewed after (suffix 1) and before (suffix 0) the attack:

1) $$\gamma = E[W(_1)] - E[W(_0)]$$

where E is the expectation operator. This is a 'sharp' RDD specification as everyone was potentially affected by the bombing from the day on which it occurred onwards via exposure to the media (see, for example, the discussion of sharp RDD in Angrist and Pischke, 2009; Lee and Lemieux, 2010). We therefore estimate an average intention to treat. Assuming a linear model for the outcome variable, this gives:

2) $$W_i = \gamma\ T_i + \beta\ f(D_i)\ T_i + \lambda\ f(D_i)\ (1-T_i) + \kappa\ V_i + u_i$$

where f(D) is a polynomial function of the running variable (measuring the distance from the cutoff) interacted with the treatment dummy *T*, to allow for different effects on either side of the cutoff. The polynomial f(.) is taken to be linear in most of our empirical specifications, but we also consider quadratics as a robustness check. The RDD design hinges on the sharp discontinuity in the outcome (individual well-being) at the cutoff (here, the day of the Boston marathon bombing) for identification. However, since we use daily data and emotional responses may vary dramatically on weekdays versus weekends (as, for instance, in Helliwell and Wang, 2014), we control for day fixed effects in the vector *V* of Equation 2.

We use the procedure in Calonico *et al.* (2017) to determine the optimal bandwidth, which is 35 days (we also test the robustness of our estimates to using smaller and larger

[15] Our running variable, which is a measure of calendar days, is continuous. See, for example, Frandsen (2018) and Kolesar and Rothe (2018) for the treatment of discrete running variables in RDD.

bandwidths, as is customary).[16] The standard errors are robust and clustered at the level of the running variable (the distance in days from the day of the Boston marathon).[17] Individuals who answered the survey on the exact day of the Boston marathon (the actual attack and the counterfactual attack) are dropped from the analysis as not all of them may be aware of the bombing, which could confound the results (however the estimates are robust to including them in the analysis).

For the RDD to be valid, we require that no other major events occurred on the day of the attack (such as a policy intervention) that may have affected the outcomes. The Boston marathon is itself an important sporting event in the US and the runners come from all over the country to participate and watch it (see Table C1 in Appendix C), while many other Americans follow it on the news. Emotional responses may therefore respond to the marathon itself, independently of any major terrorist attack. To control for this possibility, we combine the RDD estimator with a differences-in-differences estimator, using information on individuals who answered the survey in the days around the 2012 Boston marathon as an (additional) control group, as illustrated below.

2.2 Differences-in-Differences Model

Differences-in-differences models are often used in the empirical literature on the economic costs of terrorism, although finding a counterfactual not affected by the attack is challenging, which is why we also use an RDD (and other studies use panel data when available). In this framework, the implicit assumption is that terrorist attacks occur on random days. However, terrorists often plan their attacks to occur on 'special event days'. As individual outcomes may differ on such days, we use responses around the day of the 2012 Boston marathon, when there was no bombing, as a control group and combine this with the RDD model above. The underlying differences-in-differences model is:

3) $W_i = \zeta T_i * Year_i + \tau T_i + \pi Z_i + \beta \nu_i + \mu_i$,

[16] The optimal bandwidth is 35 days for negative affect (the average of sad, tired, pain, and stress feelings); it is 37 days for net affect (the difference between happy and negative affect feelings), 34 days for stress, and 47 days for happy. We opted to use the same bandwidth for all the outcomes, as well as for using a multiple of seven, to have a balanced dataset of weeks –and we control in all the regressions for day of the week (Monday to Friday) or weekend (Saturday versus Sunday) fixed effects, as it well-established that emotional well-being varies dramatically by day of the week/weekend (Helliwell and Wang, 2014). When estimating the models non-parametrically we use the optimal bandwidth. See Calonico et al. (2014) for more insights into the calculation of optimal bandwidths in RDD analyses.

[17] In an earlier version, we clustered the standard errors at the level of the individual as we had three observations (one for each of the three activities for which emotional responses were recorded) for each respondent. We now calculate individual summary measures for each of the emotional responses across the three activities, so that we only include each respondent once in the analysis.

where ζ captures the effect of the 2013 Boston marathon bombing on the outcome variable, W. The *Year* variable is one for respondents who answered the survey in 2013 and zero for 2012 respondents. *Z* is a matrix of individual characteristics, including demographic characteristics (age, age-squared, race, and gender), education, economic status, and household characteristics (number of adults in the household, number of children under age 18, and household income). We also control for whether the response day is a holiday and whether the respondent lives in an urban area (the reference category being a rural area). We control for State, year, and day (Monday to Sunday) fixed effects in the matrix *v*. The errors μ are assumed to be normally distributed.

2.3 RDD and Differences-in-Differences Combined Approach

The combination of the RDD (Equation 2) with the differences-in-differences model (Equation 3), using pooled 2012 and 2013 data, gives our preferred empirical specification:

4) $$W_i = \xi\, T_i{*}Year_i + \varphi\, f(D_i){*}T_i{*}Year_i + \varrho\, f(D_i){*}(1-T_i){*}Year_i + \alpha\, f(D_i){*}T_i + \eta\, f(D_i){*}(1-T_i) + \omega T_i + \psi Z_i + \sigma v_i + \theta_i$$

Here ξ is the coefficient of interest which captures the effect of the 2013 (labelled *Year* in the equation) Boston marathon bombing (labelled *T*) on the outcome *W*.

2.4 Heterogeneous Effects

In line with much of the empirical literature, we conduct separate analyses for those who live close to Boston and those from all other States,[18] expecting that the well-being of the former will be more affected than that of the latter. As shown in Appendix Table C1, about 23 percent of the 2013 Boston marathon runners were from Massachusetts, but all US States were represented in the race, with the largest figures coming from California (8.6 percent), New York (6.6 percent), and Illinois (4.4 percent). In addition, runners from over 70 different countries took part in the race.[19] As the sample size becomes quite small when focusing on specific States over the short period of time around the day of the attack, we do not focus only on Massachusetts, but define ‘States close by’ as Connecticut (1.9 percent of the 2013 Boston marathon runners came from Connecticut: see Table C1), Maine (0.9 percent), New Hampshire (1.8 percent), New Jersey (2.4 percent), New York (6.6 percent), Pennsylvania

[18] Note that it is not possible to analyse respondents from the Boston area separately due to sample size.

[19] While 83 percent of the race participants were US residents, 70 other countries were represented in the race, with the largest contingents coming from Canada (8 percent) and the UK (1 percent).

(3.9 percent), Rhode Island (0.9 percent), and Vermont (0.4 percent), as well as Massachusetts (23%).

We also consider different emotional responses by gender, following the literature suggesting that women may be more responsive to increased uncertainty and risk perceptions than men (Croson and Gneezy, 2009). In addition, we separate urban from rural residents, as the latter may feel less at risk of future terrorist attacks (which typically take place in urban areas). We lastly consider heterogeneity by education: if the impact of the bombing on the general population works via exacerbated fear and the media, the low-educated, who typically spend more time watching television (Stamatakis *et al.,* 2009), may be more sensitive to media exposure.

2.5 Duration of the Effects

The RDD provides an estimate of the immediate (local) effect of the attack (Angrist and Pischke, 2009; Lee and Lemieux, 2010) and is an appropriate empirical specification in this case as it is unlikely that the impact of the Boston bombing was long-lasting. However, to test for the duration of the effects, we allow the bombing's impact on well-being to vary in each of the subsequent four weeks by estimating an event study model. We also allow for differential effects in the two weeks prior to the bombing (to capture, for example, anticipation effects, although these are unlikely here). Event study models have often been applied to evaluate the impact of natural disasters and in the conflict economics literature (Sandler and Sandler, 2014). We estimate the following event study model, in which we use the 2012 data to build an additional counterfactual, in line with our methodological approach:

5) $W_i = \sum_{m=-2}^{m=4} a_m T_{i,m} Year_{i,m} + \sum_{m=-2}^{m=4} b_m T_{i,m} + c Z_i + d\, v_i + w$

with the matrix v including year, day and State fixed effects.

Here *m* denotes weeks from the Boston marathon, and we model well-being two weeks before to four weeks after the bombing, as captured by a_m (in the estimation we set the two weeks before (-2) as the excluded category, i.e. the reference period).

3. Descriptive and Graphical Evidence

We first compare the characteristics of the treatment and control samples before and after the 2012 and 2013 Boston marathon day, to test the applicability of the differences-in-differences design. Table 1a presents descriptive statistics for the pre (2012) and post (2013) treatment samples and tests of statistical differences by means of a t-test. The differences in the mean characteristics of the treatment and control samples are in general not statistically significant, indicating that the pre and post treatment sample have comparable characteristics and that a differences-in-differences model can be implemented. Moreover, we include these controls in all of our combined RDD and differences-in-differences specifications (see Equation 4 of Section 2 and the estimates reported in Table 2, specifications 3 to 9). The dscriptive statistics of the four well-being outcomes appear in Table 1b.

We provide graphical evidence of the effect of the Boston marathon bombing on the four individual well-being outcomes: happiness, stress, negative affect (the average of the individual scores for stress, sad, pain, and tiredness) and net affect (the difference between the individual scores for happiness and negative affect). For comparison purposes we also show similar figures for the outcomes before and after the 2012 Boston marathon (the counterfactual). Figures 1 and 2 plot the raw sample means (the dots), which show the average daily value of the outcome, together with the RDD estimates of the effect of the attack on the outcome (the solid lines), and the 95 percent confidence intervals around these estimates (the dashed lines).

[Insert Figures 1 & 2 here]

Figure 1 depicts a sizeable and significant drop in happiness (in the top-left panel) and a significant rise in stress (in the bottom-left panel) following the 2013 Boston marathon (when the bombing occurred). These effects are statistically significant as the standard error bounds around the RDD estimates do not cross. We also plot the comparable counterfactual using the 2012 Boston marathon estimates (the top- and bottom-right panels), which indicate no significant effect on either happiness or stress of the 2012 Boston marathon.

Figure 2 analogously shows a significant rise in negative affect (in the top-left panel) and a significant fall in net affect (in the bottom-left panel) after the 2013 Boston marathon bombing. The right-hand panels show no significant impact of the 2012 Boston marathon on these outcomes. Therefore, this suggests that the Boston bombing affected well-being and that the marathon itself does not usually impact individual well-being.

These conclusions are robust to using a quadratic fit for the RDD estimates (see Figures B4a and B4b in Appendix B). Again we detect significant falls in happiness and net affect and significant rises in stress and negative affect in the days following the bombing. Under a quadratic specification, we find some evidence that individual emotions responded to the 2012 Boston marathon, with stress and negative affect declining slightly after the race. This suggests that emotions were perhaps also impacted (possibly non-linearly) by the 2012 Boston marathon, and in the opposite direction to that for the 2013 marathon, which is plausible as there was no bombing in this year. While the estimates displayed in these figures are based on RDD models that do not control for days of the week or other individual characteristics, they motivate our empirical strategy to combine RDD with differences-in-differences in order to control for changes in well-being that may be usual in the aftermath of a national sporting event. Our estimates of the impact of the 2013 Boston marathon bombing are robust to applying either a linear or a quadratic polynomial in the running variable (see Table 2) when using our preferred parametric specification, combining RDD with differences-in-differences.

Last, we separately examine the average scores for sadness, tiredness, and pain (i.e. the other negative emotions). Figure B5 in Appendix B shows a significant rise in sadness and pain due to the bombing in 2013, but no impact in the 2012 counterfactual.

4. Estimation Results

The main results from the estimation of our preferred empirical specification (the combined RDD differences-in-differences regression of Equation 4) for the impact of the 2013 Boston marathon bombing on individual well-being appear in Table 2, alongside the main results from separate estimations of standard RDD and differences-in-differences models; and several robustness checks for our preferred specification. The duration of the impact of the bombing is summarized in Table 3, which shows the main results from an event study model where the impact of the 2013 Boston marathon bombing is allowed to vary in each of the four weeks after the bombing - while also controlling for a 2012 Boston marathon counterfactual. Table 4 then illustrates the heterogeneity of individual responses to the bombing across different dimensions (i.e. gender, education, rural/urban, geographical location, and education), by presenting the main results of our preferred specification (Equation 4) separately for different subgroups of the population.

4.1 Main Estimation Results

Specification 1a in Table 2 presents the results from a standard RDD model (Equation 2) and Specification 2 those from a standard differences-in-differences model (Equation 3). These are the techniques that have been commonly used in the literature. Specification 3 presents the results of our preferred econometric specification that combines RDD with differences-in-differences (Equation 4). We also present a number of additional specifications (4-8) as robustness checks, where we vary the RDD bandwidth, include a quadratic in the running variable, and include respondents who answered the survey on the day of the Boston marathon. We only show the estimates of the coefficient of interest: the effect of the 2013 Boston marathon bombing on the individual well-being outcomes (the full results from our preferred specification appear in Appendix Table B1).

[Insert Table 2 here]

The Specification 3 results (combining RDD and differences-in-differences) show that the 2013 Boston marathon attack led to an immediate and significant fall in happiness and a significant rise in stress. They also show an increase in negative affect and a fall in net affect. Regarding the size of these effects, the bombing produced a fall in happiness of 0.69 (individual scores can vary between 0 and 6), which corresponds to about half a standard deviation of the happiness feelings experienced in the days before the bombing. Stress rose by about the same amount. Overall, negative affect increased by 0.52 and net affect dropped by 1.2 points. This reduction in net affect is equivalent to almost two-thirds of a standard deviation of net affect in the days before the bombing. The size of these effects is thus large. The increase in stress due to the attack is more than three times larger than the difference in stress between men and women, as women experience 0.186 higher stress scores than men, on an average day, in the same data (see Table B1 in Appendix B).

The RDD approach, controlling for the day of the week, in Specification 1a yields estimates that are qualitatively similar, but slightly smaller in size, which indicates that not combing RDD with differences-in-differences may slightly underestimate the effect of the Boston marathon attack on well-being. On the other hand, the estimates from a standard differences-in-differences model (Specification 2) that includes all of the annual data from 2012 and 2013 (as is often done when using global life satisfaction questions to measure the impact of terrorism) produces no significant well-being effect. This mainly reflects that the effect of the bombing is short-lived (see below), and cannot be captured in standard differences-in-differences estimation using annual data. In this respect, RDD focusing on the immediate (local) effect of a shock is a superior approach.

Table 2 also shows that the significant and immediate drop in well-being due to the terrorist attack is robust to narrowing the bandwidth to 21 days (Specification 4) or 14 days (Specification 5), with the exception of the estimated happiness coefficient, which is no longer significant and smaller in absolute value under the two-week bandwidth. Our estimates are also robust to increasing the bandwidth, for example, to 56 days (Specification 6) and including a quadratic in the running variable (Specification 7), though under the latter specification the impact of the bombing on stress fades away. Including respondents who answered the survey on the Boston marathon day (Specification 8) does not substantially affect our conclusions, but the happiness estimate becomes slightly smaller in absolute value (it goes from 0.69 to 0.58). Last, Specification 9 shows that our findings are also robust when the standard errors are not clustered; the precision of the estimates rises, as normal. In our preferred specification, we cluster the standard errors at the level of the running variable, the days elapsed since the bombing (or, the distance in days from the marathon day).

Moreover, we also show that our conclusions are robust to estimating our preferred specification (specification 3 of Table 2), for each of the underlying outcome variables one by one (see Table B2 in Appendix B), or to estimating discrete probability models (as Bond and Land, 2018, recommend) instead of linear probability models (see Tables B2, B3a and B3b in Appendix B), or to dropping the largest US states in terms of population size (see Table B4 in Appendix B). In particular, our preferred specification is robust to dropping participants residing in California (who account for about 10% of the sample observations), New-York state (5% of sample observations) or Florida (5% of the sample observations). When setting a placebo date for the Boston marathon bombing and its counterfactual day in 2012, we find no significant impact on the outcomes (see Table B5 in Appendix B).

Overall, our results indicate a large and immediate drop in individual well-being due to the 2013 Boston marathon terrorist attack, and these findings are robust to several specification checks.

4.2 Results of the Event Study Model

We test for the persistence of the decline in individual well-being by allowing the effect of the bombing to vary in each of the four weeks following the marathon by estimating an event study model. To test that nothing else occurred in the pre-marathon period to confound our estimates, we also allow for an impact in the week before the marathon (with the second week before the marathon serving as the reference week). The estimated coefficients on the different week dummies appear in Table 3.

We find that there is no well-being effect in the week preceding the bombing, as expected, confirming the validity of our empirical approach. Moreover, we find that the impact of the bombing mostly lasts for one week only, supporting our empirical choice of RDD to capture the immediate effect of the bombing. In particular, we find a somewhat larger effect of the bombing on happiness, which drops by almost 0.86 of a standard deviation in the week following the attack. The fall in negative affect is not statistically significant, but we do find a large and significant rise in stress in the week following the attack of about half a standard deviation. The one-week fall in net affect is also comparable to the estimate from our preferred model and equates to 0.68 of a standard deviation.

In sum, the effect of the bombing is concentrated in the first week after the attack for all of the well-being outcomes considered. This may reflect the greater fear and national media coverage associated with the manhunt in the four days after the attack. The Boston marathon terrorist act then had a short-term effect on American's well-being, with normal feelings subsequently resuming, as found in Metcalfe *et al.,* (2011), whose estimates are however much smaller than ours (they examined the effect of 9/11 in the UK and the negative impact of terrorism on welfare is likely to decline with geographical distance). This does not imply that there are no longer-term negative well-being consequences of terrorist attacks as the literature on the health consequences of short-lived negative emotional shocks (as reviewed in the introduction) underlines.

[Insert Table 3 here]

4.3 Heterogeneity Results

Different groups of the population may respond to terrorism in different ways. We therefore carry out sub-group analyses by gender, geographical area of residence (States closer to Boston versus States further away), rural/urban, and education (college-educated versus less than college-educated) of our main specification 3 in Table 3. The estimated coefficients for each of these subgroups appear in Table 4.

We generally find much larger effects for women than for men (specifications 3a and 3b). For women, the bombing was associated with significantly higher stress and overall negative affect and lower net affect, while for men the bombing significantly reduced feelings of happiness and net affect. In all cases but happiness, the effect sizes are larger for women. This is consistent with the literature which finds that women are more risk-averse than men, although there is still disagreement on this (Croson and Gneezy, 2009).

We also find that those living in States geographically closer to the attack (defined as Connecticut, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont)[20] experienced a larger reduction in well-being than Americans living farther away from Boston. In particular, the estimated decline in happiness and net affect is more than twice as large for Americans living somewhat closer to Boston than for the average American. We find no impact on stress or negative affect for those living closer to Boston (see specification 3c in Table 4). These findings may be driven by the small sample size as the number of respondents located in States close to Boston was only 700 pooling together 2012 and 2013 data. We also find that the Boston marathon attack only slightly affected the well-being of those living far away from Boston (see specification 3d in Table 4), with no significant impact on happiness and stress, and negative affect being only significant at the ten per cent level. Therefore, our estimates indicate that those living closer to Boston and those living farther away reacted differently to the attack, in contrast with earlier findings that terrorist attacks can spill over to impact the well-being of those geographically distant (e.g. Pfefferbaum *et al.,* 2001; Metcalfe *et al*., 2011).

Next we consider the impact on urban and rural respondents as terrorism may especially affect the well-being of urban residents who feel more at risk from future attacks[21] (terrorist attacks typically take place in urban areas to maximize damage). Specifications 3e and 3f in Table 4 show the well-being estimates of the bombing for urban and rural residents, respectively. The attack has a strong effect on the happiness, stress, negative affect, and net affect of urban residents, but no significant impact on rural residents.

Finally, we consider effects for groups with different levels of education. If, for example, the lower-educated spend more time watching television, or are more responsive to fear conditioning, then we would expect the bombing to have a greater effect on them. We find that the impact of the bombing has no significant effect on the well-being of the college educated; yet there is a decline in net affect for those with less than a college education, driven by an increase in stress for the high-school educated and by a decline in happiness for those with less than a high-school education (specifications 3g, 3h and 3i in Table 4). The sign and sizes of the estimated responses are comparable for these two groups (i.e., high school or less than high school), suggesting that cell size may be responsible for the differences in statistical significance across the responses of these two subgroups. In contrast, all the estimates are much smaller and not statistically significant for college graduates. This

[20] We would ideally like to restrict our attention to New England, excluding New York, Pennsylvania, and New Jersey, but the sample size drops dramatically when we do so.
[21] These are the only two residential categories available in the ATUS-WB data. We do not have information on the size of the city of residence.

reinforces the argument that the impact of terrorism spreads via feelings of fear of future attacks which may be more diluted by extra years of education.

[Insert Table 4 here]

4.4 Results for Other Outcomes

Terrorist attacks affect individual welfare and behavior mostly via their effects on fear, uncertainty, and risk aversion (Becker and Rubinstein, 2011) and as such they may reduce the time devoted to activities performed outside the home, at least in the short-term (see Section 1.2 for a discussion). Table 5 shows the estimates, using our preferred combined RDD differences-in-differences specification, of the impact of the Boston bombing on time spent on sleep, active leisure (e.g. exercise), watching television, doing household chores, childcare, and hours of market work. The bombing has no significant impact on any of these activities, with the exception of market hours which fall by about half an hour per day (in line with earlier work by Abadie and Gardeazabal, 2008, Brodeur, 2018). Note that there may be an issue with the ATUS-WB survey measuring time spent on main activities rather than secondary activities, as much of the time spent watching television may be a secondary activity rather than the main activity.

To further quantify our effects, Table 5 shows that the effect of the bombing on daily hours of market work is -0.609, and we found that the impact of the bombing lasted about one week. With an average wage of $19.21 in 2013, this corresponds to an income loss per person of just under $60. As our coefficient applies to the whole of the US, multiplying by the 2013 US population (of 316 million) produces an income effect of $18.5BN (almost 6% of US weekly GDP in 2013, or over 0.1% of annual GDP). While the economic impact is potentially large, the correlational nature of this analysis should be noted.

[Insert Table 5 here]

5. Discussion and Conclusions

The negative effects of terrorism on both aggregate economic growth and individual well-being (using broader life satisfaction questions) have been underlined in a small existing literature (e.g. Abadie and Gardeazabal, 2008; Metcalfe *et al.,* 2011). We contribute to this literature by evaluating the impact of the 2013 Boston marathon bombing using daily well-being measures taken from unique diary data for a large representative sample of the US population from the American Time Use Survey and Well-Being module. This cross-sectional survey uses the day reconstruction method to measure experienced well-being on a daily basis for over 11,000 Americans each year. Experienced well-being measures are generally thought to be less subject to framing effects compared to global measures of life satisfaction (Doyle *et al.,* 2015), and are particularly suitable for evaluating the immediate welfare impact, if any, of unexpected and traumatic events. These well-being data were collected using a randomized procedure and we show that the survey was run continuously in the days around the 2013 Boston marathon bombing. Therefore, this provides a unique quasi-natural experimental framework to test the effects of an isolated act of terrorism on individual well-being.

Terrorist attacks are likely to be planned to maximize the number of victims and to attract the most attention, while individual emotions and behavior may differ during major sporting events. Thus, we rely on a Regression Discontinuity Design, in which the running variable is the distance in days elapsed before and after the Boston marathon day, to identify the immediate impact of the bombing on individual well-being; this is combined with a differences-in-differences model that uses answers to the surveys around the days of the 2012 Boston marathon as an additional counterfactual, to control for any variation in well-being that may be usual at this time of year. This represents a methodological contribution to the empirical literature on the economic impact of terrorism, which has to date assumed that the day of the attack is a normal day.

We find that the Boston marathon bombing had a sharp negative impact on experienced well-being. On average, happiness immediately dropped by half a standard deviation and stress increased by about the same amount. The other negative emotions, as summarized by negative affect also increased, leading to a large and significant drop in overall net affect, corresponding to almost two-thirds of a standard deviation. This is larger than the 7 percent of a standard deviation decline found in Metcalfe *et al.* (2011), which is plausible considering their focus on the 9/11 attacks in the US on UK residents – as the effect of terrorism on well-being is likely to decline with psychological and geographical distance. We also find evidence of considerable heterogeneity in the responses to the Boston marathon bombing by gender, education, urban residency, and geographical proximity to the place of the attack. The size and direction of these effects are consistent with our hypothesis that women, those living closer to the attack and in urban areas, and those with less education are more impacted by the bombing.

Taking an event study approach, and controlling for the 2012 counterfactual, we conclude that the negative well-being effects of the Boston marathon bombing had largely dissipated by the second week after the attack. This is in line with Krueger (2007) who finds that the 9/11 terrorist attack led to lower enthusiasm and greater sadness for seven days after the attack, using similar experienced well-being data from Wisconsin only. It is also consistent with Metcalfe *et al.* (2011) who find no long-term impact of the 9/11 attack on subjective well-being in the UK. Thus, our results are consistent with the literature regarding the short-term nature of terrorist attacks on well-being. Our event study estimates also show no significant changes in well-being in the week preceding the Boston marathon, which corroborates the robustness of our empirical approach. Similar to most reduced-form work, we cannot claim external validity, such that similar effects would be observed for other isolated terrorist attacks. However, as our estimates are similar to those in the scant earlier literature, they may also hold for other terror attacks, with the channel being the fear and risk-aversion generated by the uncertainty of future terrorist events (Becker and Rubinstein, 2011).

While the well-being effects of the Boston marathon bombing do not appear to be long-lasting, the immediate effect is large and may lead to adverse health and economic consequences. The literature has shown that stress can negatively affect the health outcomes of current and future generations (Currie and Rossin-Slater, 2013; Black *et al.,* 2016; Cawley *et al.,* 2017), as well as economic decision making (Delaney *et al.,* 2014). There is also evidence that repeated media exposure to multiple terrorist attacks may lead to increases in long-term stress and trauma-related disorders (Holman *et al.,* 2014). This suggests that the increasing frequency, and thus reporting, of terrorist acts in Europe and the US may potentially lead to higher levels of stress-related diseases in the long term. However, we would need to conduct long-term follow-up analysis of terrorist attacks to test this hypothesis. If supported, then efforts to reduce cues to the threat of terrorism by, for example, limiting the amount of news coverage devoted to terrorist acts or encouraging individuals to limit the amount of time spent exposed to such media, may serve to protect against the possible long-term consequences of terrorism on individual well-being.

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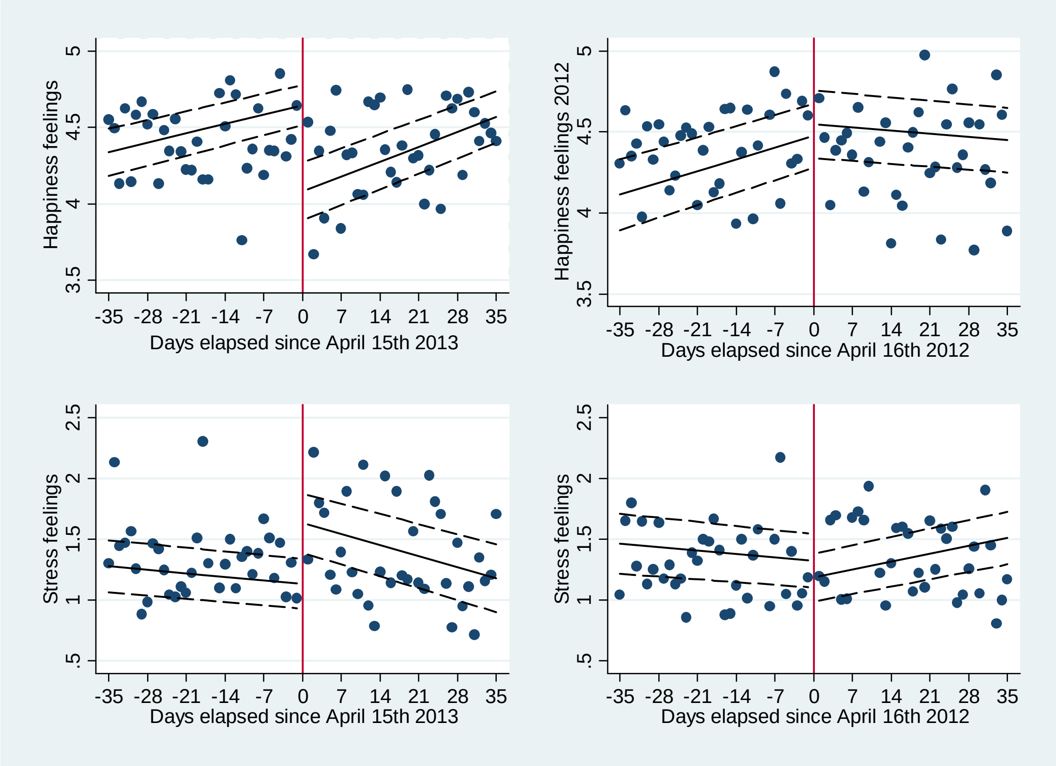
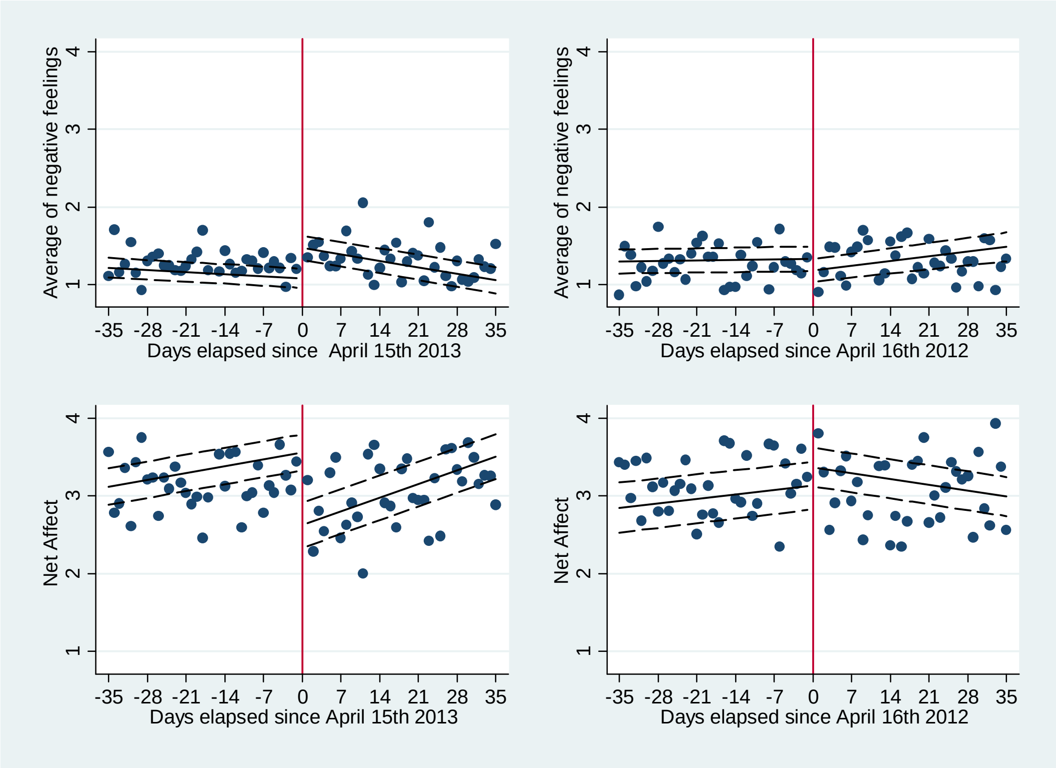
Figure 1 – Happiness and Stress before and after the Boston marathon



Notes: The graphs plot, respectively, average daily happiness (top panel) and stress (bottom panel) against the days elapsed before (negative values) or after (positive values) April 15th 2013 (left panel graphs), corresponding to the 2013 Boston marathon day, when the bombing occurred, and April 16th 2012 (right panel graphs), the day of the 2012 Boston marathon that serves as a counterfactual in our RDD differences-in-differences models. Emotional feelings of happiness (or stress) are averaged over those experienced during each of the three diary activities (selected randomly out of those reported in the diary) by summing up and dividing by three. They are measured on a scale of 0 to 6. The dots correspond to the sample means. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week), as is standard in RDD. The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Figure 2 – Average of Negative Affect (stress, sad, pain and tiredness) and Net Affect before and after the Boston marathon



Notes: The graphs plot, respectively, average daily negative affect (top panel) and net affect (bottom panel) against the days elapsed before (negative values) or after (positive values) April 15th 2013 (left panel graphs), corresponding to the 2013 Boston marathon day, when the bombing occurred, and April 16th 2012 (right panel graphs), the day of the 2012 Boston marathon that serves as a counterfactual in our RDD differences-in-differences models. Each negative emotion (stress, sadness, pain, and tiredness) experienced during each of three diary activities (selected randomly out of those reported in the diary) is averaged over the three activities and, next, the four average negative emotions are summed up and divided by four. Emotions are measured on a scale of 0 to 6. Net affect is the difference between the positive (happy) and negative (the average of stress, sad, tired, in pain) emotions, for each of the three activities, and further averaged by summing up and dividing by three. The dots correspond to the sample means. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week), as is standard in RDD. The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Table 1a – T-tests of Mean Differences in the Characteristics of the Treatment and Control Samples

	Boston marathon, 2013		Boston marathon, 2012		T-test, before 2013 vs after 2013	T-test, before 2013 vs before 2012	T-test, after 2013 vs after 2012
	1-35 days before	1-35 days after	1-35 days before	1-35 days after			
Age	48.48 (17.96)	47.71 (17.75)	48.10 (17.42)	48.84 (18.21)	0.76 (0.73)	0.38 (0.73)	-1.13 (0.75)
Woman	0.54 (0.50)	0.55 (0.50)	0.57 (0.49)	0.54 (0.50)	-0.01 (0.02)	-0.03 (0.02)	0.004 (0.02)
High school	0.23 (0.42)	0.27 (0.44)	0.26 (0.44)	0.25 (0.43)	-0.04 (0.02)**	-0.03 (0.018)	0.018 (0.018)
Less than high school	0.15 (0.35)	0.13 (0.34)	0.13 (0.33)	0.14 (0.35)	0.016 (0.014)	0.02 (0.01)	-0.007 (0.014)
White	0.79 (0.40)	0.79 (0.40)	0.78 (0.01)	0.80 (0.40)	-0.005 (0.016)	0.007 (0.016	-0.005 (0.016)
Black	0.15 (0.36)	0.14 (0.35)	0.15 (0.35)	0.14 (0.34)	0.010 (0.014)	0.005 (0.015)	0.005 (0.014)
Urban area resident	0.83 (0.38)	0.83 (0.38)	0.82 (0.38)	0.83 (0.38)	-0.001 (0.015)	0.005 (0.016)	0.001 (0.01)
Living in states close to Boston	0.16 (0.37)	0.16 (0.37)	0.16 (0.36)	0.16 (0.37)	-0.001 (0.015)	0.006 (0.015)	0.003 (0.015)
No. dependent children aged< 18	0.58 (0.49)	0.58 (0.49)	0.60 (0.49)	0.63 (0.48)	-0.001 (0.02)	-0.02 (0.02)	-0.05(0.02)**
No. of children	0.82 (1.11)	0.85 (1.16)	0.79 (1.08)	0.78 (1.18)	-0.023 (0.047)	0.031 (0.045)	0.06 (0.05)
Employed	0.59 (0.49)	0.59 (0.49)	0.58 (0.49)	0.57 (0.49)	-0.005 (0.02)	0.006 (0.02)	0.02 (0.02)
Income	59370 (43043)	58919 (44221)	59335 (42882)	57502 (41993)	450.76 (1799)	34.48 (1780)	1416.8 (1788)
Observations	*1200*	*1154*	*1132*	*1173*			

Notes: The figures are sample means with standard deviations in parentheses. * in Column 5 indicates a statistically significant mean difference between the given characteristic across the 2013 "before" and "after" samples. * in Column 6 indicates a statistically significant mean difference between the given characteristic across the 2012 "before" and the 2013 "before" samples. * in Column 7 indicates a statistically significant mean difference between the given characteristic across the 2012 "after" and the 2013 "after" samples. The observations are weighted using ATUS-WB weights. The total number of observations is 4659, of which 2354 correspond to 2013 and 2305 to 2012.

Table 1b – Descriptive Statistics of the Individual Well-being Outcomes

	Boston marathon, 2013		Boston marathon, 2012	
	1-35 days before	1-35 days after	1-35 days before	1-35 days after
Happy	4.49 (1.23)	4.30 (1.29)	4.30 (1.35)	4.51 (1.2)
Stress	1.20 (1.37)	1.42 (1.43)	1.39 (1.38)	1.36 (1.36)
Negative Affect	1.15 (0.96)	1.28 (0.99)	1.31 (0.98)	1.33 (1.08)
Net Affect	3.34 (1.81)	3.02 (1.88)	3.00 (1.88)	3.19 (1.87)

Notes: The figures are sample means with standard deviations in parentheses. The observations are weighted using ATUS-WB weights.

Table 2 – The effect of the Boston Marathon Bombing on Individual Well-being

	Happy	**Stress**	**Negative Affect**	**Net Affect**
Mean month before (standard deviation)	4.49 (1.23)	1.20 (1.37)	1.15 (0.96)	3.34 (1.81)
1a) RDD (Equ. 2)	-0.629***	0.475*	0.417***	-1.028***
Bandwidth 35 days, 2013 data	(0.134)	(0.260)	(0.143)	(0.222)
Observations	2,124	2,142	2,110	2,095
R-squared	0.035	0.035	0.025	0.035
1b) RDD (non-parametric estimates)	-0.608***	0.609**	0.486***	-1.013***
Optimal bandwidth, 2013 data	(0.139)	(0.310)	(0.148)	(0.212)
2) Diff-in-Diff (Equ. 3)	-0.0842	0.0763	0.0381	-0.125
Pooled 2012 & 2013 data	(0.0789)	(0.0837)	(0.0673)	(0.125)
Observations	20,902	21,074	20,879	20,712
R-squared	0.032	0.055	0.063	0.046
3) RDD* Diff-in-Diff (Equ. 4)	-0.696***	0.691*	0.526**	-1.234***
Bandwidth 35 days, 2012 & 2013 data	(0.246)	(0.379)	(0.200)	(0.341)
Observations	4,366	4,396	4,341	4,316
R-squared	0.062	0.109	0.109	0.083
4) RDD* Diff-in-Diff (Equ. 4)	-0.712**	0.993**	0.726***	-1.407***
Bandwidth 21 days, 2012 & 2013 data	(0.296)	(0.474)	(0.232)	(0.427)
Observations	2,708	2,729	2,693	2,675
R-squared	0.089	0.140	0.108	0.105
5) RDD* Diff-in-Diff (Equ. 4)	-0.472	1.261*	0.697**	-1.107**
Bandwidth 14 days, 2012 & 2013 data	(0.389)	(0.616)	(0.285)	(0.490)
Observations	1,877	1,891	1,870	1,856
R-squared	0.138	0.159	0.151	0.155
6) RDD* Diff-in-Diff (Equ. 4)	-0.767***	0.607*	0.503**	-1.280***
Bandwidth 56 days, 2012 & 2013 data	(0.255)	(0.323)	(0.211)	(0.397)
Observations	6,571	6,615	6,543	6,502
R-squared	0.050	0.091	0.121	0.088
7) RDD* Diff-in-Diff (Equ. 4)	-0.676**	0.783	0.518**	-1.187***
Bandwidth 56 days, 2012 & 2013 data, & quadratic function of the running variable	(0.316)	(0.507)	(0.253)	(0.445)
Observations	6,571	6,615	6,543	6,502
R-squared	0.055	0.093	0.126	0.094
8) RDD* Diff-in-Diff (Equ. 4)	-0.579**	0.627*	0.521***	-1.111***
Bandwidth 35 days, 2012 & 2013 data, including obs. on the day of the marathon.	(0.262)	(0.350)	(0.184)	(0.344)
Observations	4,420	4,451	4,395	4,369
R-squared	0.063	0.110	0.111	0.085
9) RDD* Diff-in-Diff (Equ. 4)	-0.696**	0.691**	0.526**	-1.234***
Bandwidth 35 days, 2012 & 2013 data, standard errors are robust but not clustered	(0.300)	(0.311)	(0.206)	(0.420)
Observations	4,366	4,396	4,341	4,316
R-squared	0.062	0.106	0.106	0.082

Notes: Robust standard errors in parentheses. Standard errors are clustered at the level of the running variable (days elapsed) in all models but specification 9. Weights are applied. The RDD models include controls for day of the week (the latter are not included in specification 1b). The RDD diff-in-diff models include other controls, see Equations Section 2. *** p<0.01, ** p<0.05, * p<0.1

Table 3 – The duration of the Effect of the Boston Marathon Bombing on Individual Well-being

	Happy	**Stress**	**Negative Affect**	**Net Affect**
One-week before	-0.458	-0.213	-0.222	-0.205
	(0.319)	(0.311)	(0.224)	(0.418)
One-week after	-1.083***	0.716**	0.290	-1.329***
	(0.350)	(0.321)	(0.232)	(0.451)
Two-weeks after	-0.702*	-0.126	0.0568	-0.785
	(0.377)	(0.349)	(0.254)	(0.479)
Three-weeks after	-0.331	-0.145	-0.359	0.0734
	(0.328)	(0.310)	(0.263)	(0.462)
Four-weeks after	-0.502	0.130	-0.144	-0.418
	(0.352)	(0.310)	(0.225)	(0.452)
Observations	2,800	2,820	2,781	2,763
R-squared	0.088	0.147	0.146	0.114

Notes: The model corresponds to Equation 5. The second week before the marathon (in either 2012 or 2013) is the reference period. The models include controls (see Equation 5). Robust standard errors in parentheses. Weights are applied. *** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 4 – Heterogeneous Effects of the Boston Marathon Bombing on Individual Well-being

	Happy	**Stress**	**Negative Affect**	**Net Affect**
Mean month before – women (st. dev.)	4.55 (1.21)	1.22 (1.40)	1.21 (1.03)	3.35 (1.87)
Mean month before – men (st. dev.)	4.53 (1.23)	1.07 (1.31)	1.04 (1.89)	3.49 (1.74)
Mean month before – States nearby (st. dev.)	4.36 (1.15)	1.30 (1.45)	1.19 (0.95)	3.16 (1.83)
Mean month before – other States (st. dev.)	4.57 (1.23)	1.20 (1.34)	1.11 (0.97)	3.46 (1.80)
Mean month before – metropolitan residents (st. dev.)	4.41 (1.27)	1.30 (1.47)	1.28 (1.09)	3.14 (1.98)
Mean month before – college education (st. dev.)	4.35 (1.22)	1.38 (1.46)	1.24 (0.99)	3.13 (1.88)
Mean month before – high school (st. dev.)	4.53 (1.31)	1.09 (1.40)	1.23 (1.12)	3.29 (1.96)
Mean month before – less than high school (st. dev.)	4.52 (1.28)	1.19 (1.46)	1.31 (1.17)	3.20 (2.07)
3a) RDD* Diff-in-Diff, Women	-0.633	1.546***	0.939**	-1.665**
Bandwidth 35 days, 2012 & 2013 data	(0.383)	(0.571)	(0.380)	(0.681)
Observations	2,412	2,423	2,401	2,389
R-squared	0.102	0.130	0.109	0.109
3b) RDD* Diff-in-Diff, Men	-0.623*	0.106	0.187	-0.757*
Bandwidth 35 days, 2012 & 2013 data	(0.353)	(0.365)	(0.231)	(0.435)
Observations	1,954	1,973	1,940	1,927
R-squared	0.112	0.198	0.205	0.155
3c) RDD* Diff-in-Diff, States closeby	-1.752***	0.769	0.647	-2.362**
Bandwidth 35 days, 2012 & 2013 data	(0.596)	(0.739)	(0.544)	(1.017)
Observations	702	713	704	695
R-squared	0.242	0.321	0.344	0.317
3d) RDD* Diff-in-Diff, Other States	-0.228	0.366	0.338*	-0.577*
Bandwidth 35 days, 2012 & 2013 data	(0.293)	(0.302)	(0.185)	(0.329)
Observations	3,664	3,683	3,637	3,621
R-squared	0.056	0.093	0.084	0.068
3e) RDD* Diff-in-Diff, Metropolitan area	-0.821***	0.745*	0.478**	-1.287***
Bandwidth 35 days, 2012 & 2013 data	(0.267)	(0.417)	(0.185)	(0.332)
Observations	3,608	3,634	3,595	3,573
R-squared	0.072	0.120	0.114	0.093
3f) RDD* Diff-in-Diff, Rural area	0.652	0.0878	0.576	-0.171
Bandwidth 35 days, 2012 & 2013 data	(0.464)	(0.412)	(0.409)	(0.668)
Observations	758	762	746	743
R-squared	0.271	0.312	0.325	0.313
3g) RDD* Diff-in-Diff, College education	-0.289	0.0932	0.000336	-0.280
Bandwidth 35 days, 2012 & 2013 data	(0.470)	(0.400)	(0.260)	(0.628)
Observations	1,913	1,926	1,914	1,904
R-squared	0.095	0.158	0.135	0.122
3h) RDD* Diff-in-Diff, High school	-0.676	0.796	0.815*	-1.673*
Bandwidth 35 days, 2012 & 2013 data	(0.568)	(0.688)	(0.476)	(0.847)
Observations	1,097	1,104	1,078	1,073
R-squared	0.220	0.216	0.203	0.210
3i) RDD* Diff-in-Diff, Less than high school	-0991*	1.186	0.519	-1.574*
Bandwidth 35 days, 2012 & 2013 data	(0.552)	(0.731)	(0.437)	(0.888)
Observations	491	498	485	480
R-squared	0.327	0.263	0.281	0.284

Notes: Robust and clustered standard errors in parentheses. The specification corresponds to Equation 4.
*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 5 – The effect of the 2013 Boston Marathon Bombing on Other Outcomes

	Sleep	**Active leisure**	**Television**	**Household work**	**Childcare**	**Market hours**
Mean month before (st. dev.) Hours per day	8.64 (2.28)	0.29 (0.86)	2.69 (2.77)	1.58 (2.11)	0.40 (1.11)	3.10 (4.15)
RDD* Diff-in-Diff (Equ. 4) Bandwidth 35 days, 2012 & 2013 data	0.0285	-0.162	0.430	-0.382	-0.0567	-0.609**
	(0.302)	(0.136)	(0.370)	(0.310)	(0.126)	(0.269)
Observations	4,842	4,842	4,842	4,842	4,842	4842
R-squared	0.124	0.078	0.199	0.140	0.283	0.519

Notes: The outcome variables are measured in hours per day. Hours of work are unconditional of being employed and set to zero for unemployed and inactive. Robust standard errors in parentheses. Standard errors are clustered at the level of the running variable (days elapsed). Weights are applied throughout. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix A The ATUS WB Survey

ATUS Well-Being Questions

The Well-being Module begins with an introductory screen explaining the purpose of the module questions, and then proceeds to the screen asking how the respondent felt during the selected activities.

QUESTIONS 1 THROUGH 7

Now I want to go back and ask you some questions about how you felt yesterday. We're asking these questions to better understand people's health and well-being during their daily lives. As before, whatever you tell us will be kept confidential. The computer has selected 3 time intervals that I will ask about.

Between [STARTTIME OF EPISODE] and [STOPTIME OF EPISODE] yesterday, you said you were doing [ACTIVITY]. The next set of questions asks how you felt during this particular time.

Please use a scale from 0 to 6, where a 0 means you did not experience this feeling at all and a 6 means the feeling was very strong. You may choose any number 0,1,2,3,4,5 or 6 to reflect how strongly you experienced this feeling during this time.

1.	Happy	First, from 0 – 6, where a 0 means you were not happy at all and a 6 means you were very happy, how happy did you feel during this time?
2.	Tired	From 0 – 6, where a 0 means you were not tired at all and a 6 means you were very tired, how tired did you feel during this time?
3.	Stressed	From 0 – 6, where a 0 means you were not stressed at all and a 6 means you were very stressed, how stressed did you feel during this time?
4.	Sad	From 0 – 6, where a 0 means you were not sad at all and a 6 means you were very sad, how sad did you feel during this time?
5.	Pain	From 0 – 6, where a 0 means you did not feel any pain at all and a 6 means you were in severe pain, how much pain did you feel during this time if any?

[THE ORDER OF THE AFFECTIVE DIMENSIONS (ITEMS 1-5) WAS RANDOMIZED BY RESPONDENT].

Respondents were also asked the following question.

	Meaningful	From 0 to 6, how meaningful did you consider what you were doing? 0 means it was not meaningful at all to you and a 6 means it was very meaningful to you.

This question was not randomized. We analyzed it in an earlier version of this paper where we considered meaningfulness as a positive well-being dimension together with happiness. Meaningfulness has received attention by psychologists in relation to engagement/disengagement in employment (Kahn, 1990; May *et al.,* 2004). It also appears as a core element in eudaimonic measures of functional wellbeing, alongside autonomy, competence, personal growth, positive relationships, self-acceptance and engagement (Deci and Ryan, 2000, and Ryff, 1989). We estimated the impact of the Boston bombing on meaningfulness using our preferred specification and found that it did not respond to the bombing, contrary to the other emotions (see Figure B6 in the Appendix).

ATUS-WB data consistency checks

While the ATUS data has been widely used in the economics literature, the WB data has been less utilized. We test the reliability of the well-being data by carrying out a number of checks to ensure that responses to the questions were not randomly given and that respondents paid attention and understood the questions (see, for example, Meade and Craig, 2012, on the identification of careless responses in lengthy surveys; one advantage of the ATUS-WB supplement is that it is short and focused on emotional well-being). All our reliability tests are based on the two years of data used in the analysis of the full sample (2012 & 2013). We also run separate RDDs and other consistency tests for the data collected in the analysis period around the days of the Boston marathon (see the next Appendix and the Descriptive and Graphical checks in the paper).

The survey designers explicitly state that the WB data should not be used to investigate how participants felt in relation to the specific activity reported (Bureau of Labor Statistics. 2014, page 6, fourth paragraph). The day reconstruction method aims to build an overall measure of the respondent's well-being for the day as a whole; as such, we combine emotional responses to the three reported activities to generate indices of negative affect and net affect, as well as focusing on the specific emotions of happiness and stress.

To test whether participants paid attention to the questions being asked, we examine whether the respondents gave the same answer for each of the five emotions (last column of Table A1). This applied to only 0.05% of the sample: 0.0003% always answered zero or one, 0.0004% always answered five or six, and 0.0009% always answered three or four (last column of Table A1). Moreover, only 0.0007% of the sample gave a different answer for each of the five emotions asked across the three different activities. As many of these emotions are correlated with each other (see Tables A2 and A3), this also indicates that the respondents did not answer randomly. This suggests that the WB data are reliable.

Table A1 – Values reported for the five well-being outcomes

All zeros or ones	0.003
	(0.051)
All five or six	0.0004
	(0.019)
All three or four	0.0009
	(0.029)
All the same value	0.049
	(0.216)
All different from each other	0.0007
	(0.027)
Observations	20741

Note: ATUS-WB data for 2012 and 2013. We report means and standard deviations based on a series of dummies for all the emotions reported for the three activities all being equal to one or zero, five or six, three or four, or all the same value, or all different from each other.

Table A2 reports the correlations for the same emotions across different activities. It shows that emotions are strongly correlated across different activities, with the correlation between the three happiness answers being, for example, well above 0.5. The correlations between the different emotions for the same activity are smaller (see Table A3), although also non-negligible. In particular, all of the negative emotions (sadness, stress, tiredness, and pain) are negatively correlated with the happiness associated with the activity (see Table A3), while the negative emotions are positively correlated with each other. Respondents were thus globally able to distinguish positive from negative feelings. This is in line with evidence on the reliability of these data from other work (see Lee *et al.,* 2016).

One potential concern with the day reconstruction method (DRM) is that respondents may not accurately recall the emotions that they experienced the previous day (although this would arguably bias our estimates towards zero). A number of contributions have considered this issue by comparing the DRM scores to those provided in real time using experienced sampling methods and all of these find a reasonably high degree of convergence between the scores (Bylsma *et al.,* 2011; Dockray *et al.,* 2010; Kahneman *et al.,* 2004; Kim *et al.,* 2013; Miret *et al.,* 2012). In addition, Daly *et al*. (2010) find a positive correlation between the DRM measures of negative affect and fluctuations in heart rate, which is an objective indicator of psychological stress. There is thus a substantial degree of concordance across analyses demonstrating that the DRM provides a reliable means of measuring emotional states. See Diener and Tay (2014) for a critical review of DRM research.

Table A2 – Correlation between the same emotions across the three different activities (denoted “1”, “2” and “3”).

	Happy Activity 1	Sad Activity 1	Stress Activity 1	Pain Activity 1	Tired Activity 1
Happy Activity 2	0.553*				
Sad Activity 2		0.592*			
Stress Activity 2			0.547*		
Pain Activity 2				0.754*	
Tired Activity 2					0.565*
Observations	*20902*	*21038*	*21075*	*21090*	*21055*
	Happy Activity 1	Sad Activity 1	Stress Activity 1	Pain Activity 1	Tired Activity 1
Happy Activity 3	0.522*				
Sad Activity 3		0.568*			
Stress Activity 3			0.529*		
Pain Activity 3				0.725*	
Tired Activity 3					0.505*
Observations	*20902*	*21038*	*21075*	*21090*	*21055*
	Happy Activity 3	Sad Activity 3	Stress Activity 3	Pain Activity 3	Tired Activity 3
Happy Activity 2	0.550*				
Sad Activity 2		0.612*			
Stress Activity 2			0.561*		
Pain Activity 2				0.765*	
Tired Activity 2					0.586*
Observations	*20902*	*21038*	*21075*	*21090*	*21055*

Note: ATUS-WB data for 2012 and 2013. The correlation coefficient is the Spearman rank correlation between, for example, the respondent’s feelings of happiness in the first activity and their feelings of happiness in the second activity, with a star denoting a Bonferroni significance level of 5%.

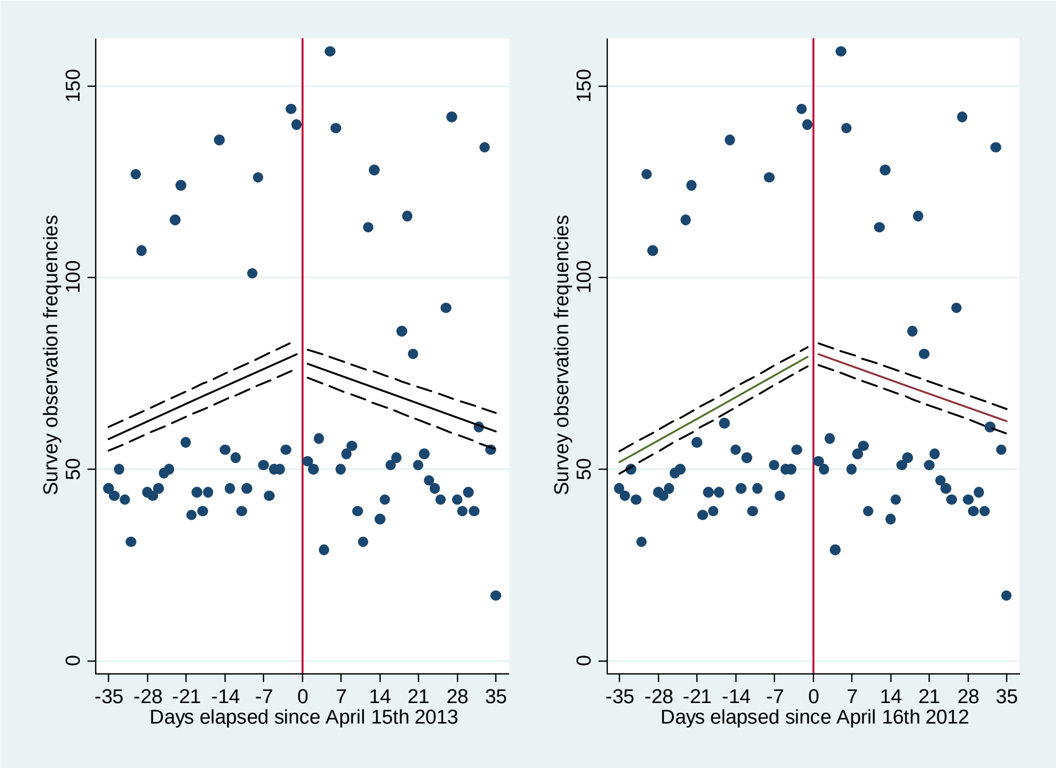
Table A3 – Correlation across emotions for the same activity

Activity 1	Happy	Sad	Stress	Pain	Tired
Happy		-0.326*	-0.357*	-0.166*	-0.227*
Sad			0.452*	0.320*	0.270*
Stress				0.278*	0.377*
Pain					0.308*
Tired					
Activity 2	Happy	Sad	Stress	Pain	Tired
Happy		-0.330*	-0.359*	-0.165*	-0.210*
Sad			0.469*	0.342*	0.282*
Stress				0.298*	0.384*
Pain					0.326*
Tired					
Activity 3	Happy	Sad	Stress	Pain	Tired
Happy		-0.328*	-0.356*	-0.164*	-0.202*
Sad			0.488*	0.345*	0.265*
Stress				0.312*	0.369*
Pain					0.323*
Tired					

Note: ATUS-WB data for 2012 and 2013. The correlation coefficient is the Spearman rank correlation between, for example, feelings of happiness in the first activity and feelings of sadness in the first activity, with a star denoting a Bonferroni significance level of 5%.

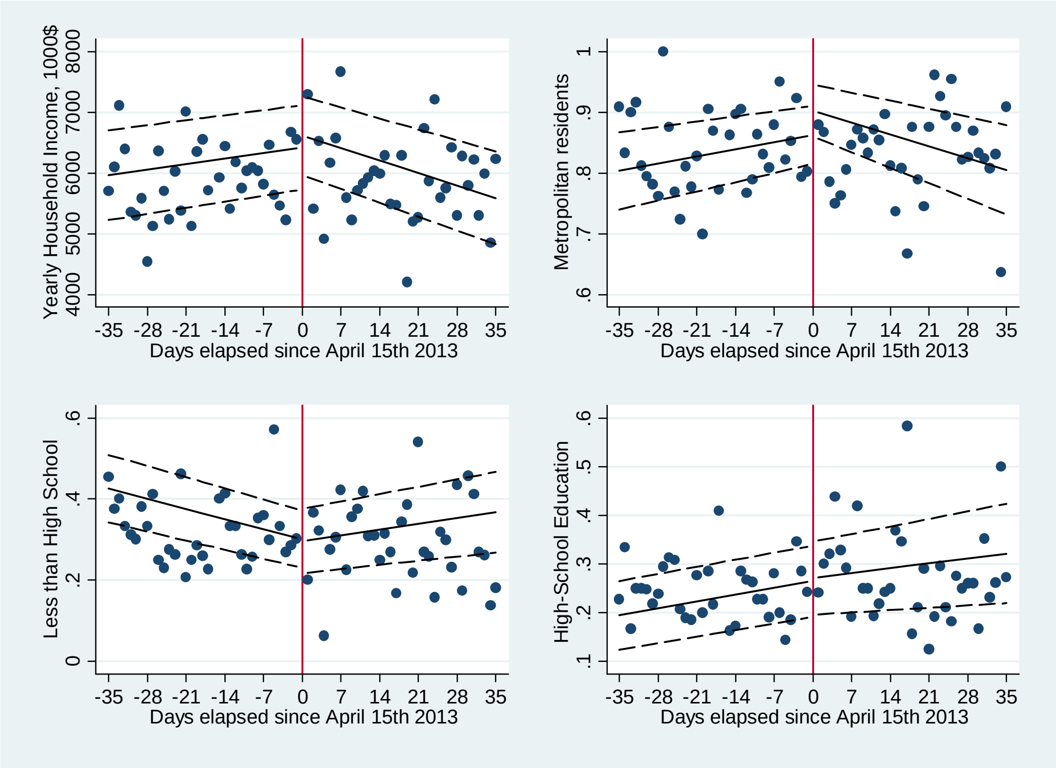
Appendix B

Figure B1 – Responses to the ATUS-WB survey in the days before and after the Boston marathon



Note: The graphs plot the survey response frequency against the days elapsed before (negative values) or after (positive values) April 15th 2013, which corresponds to the 2013 Boston marathon day, when the bombing occurred (left-hand graph) or April 16th 2012, which corresponds to the 2012 Boston marathon day, our counterfactual. The dots correspond to the sample means each day. The unbroken line is fitted through the triangular kernel estimates (with a bandwidth of 35 days; without controlling for any explanatory variables, as is standard in RDD). The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates. The graphs indicate that participation in the survey was not discontinuous at the cut-off and therefore, the regression discontinuity design is valid. We also test for this by running parametric RDD regressions (Equation 2 in the Method section) in which the outcome variable is the frequency of observations: the estimated coefficient are, respectively, 4.84 (with a standard error of 6.52) for 2013; and 7.93 (with a standard error of 7.20) for 2012.

Figure B2 – Control variables in the days before and after the 2013 Boston marathon: income, metropolitan area of residence, and education

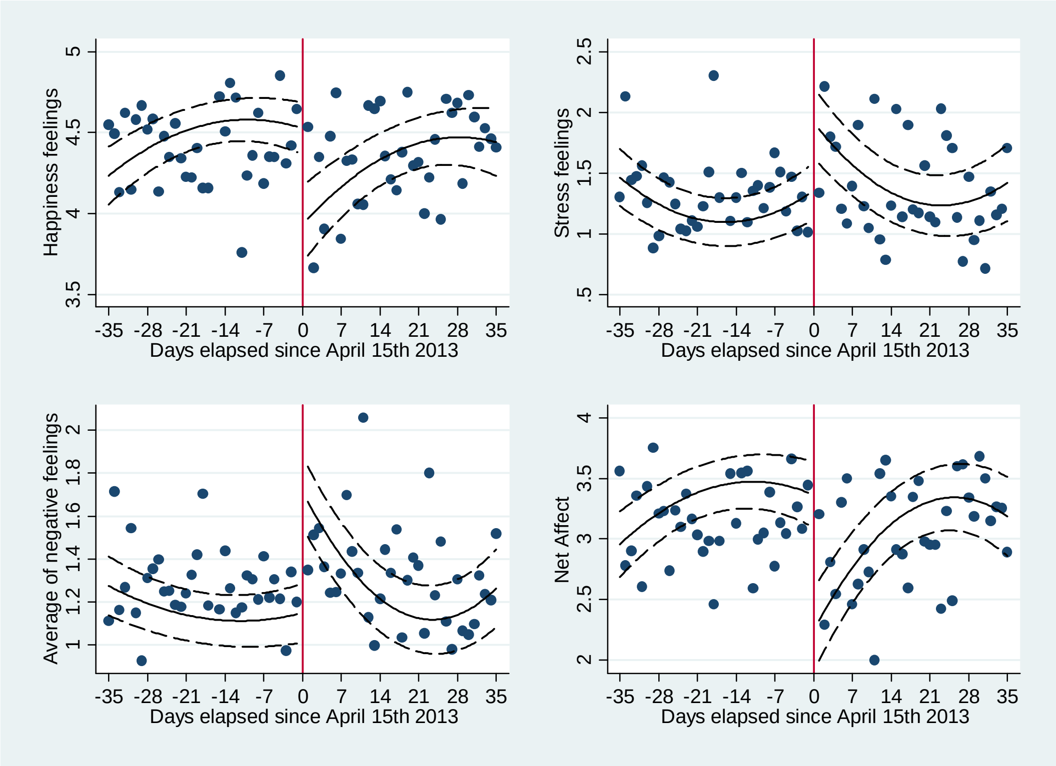


Note: The graphs plot average household income, the proportion of respondents living in a metropolitan area (versus a rural area), the proportion of respondents who completed high-school and those that did not, in each of the days elapsed before (negative values) or after (positive values) April 15th 2013, which corresponds to the day of the 2013 Boston marathon bombing. The dots correspond to the sample means each day. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week), as is standard in RDD. The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates. The graphs indicate that these explanatory variables are not discontinuous at the cut-off and therefore, the regression discontinuity design is valid.

Figure B3 – Control variables in the days before and after the 2013 Boston marathon: gender, age, race, and number of children

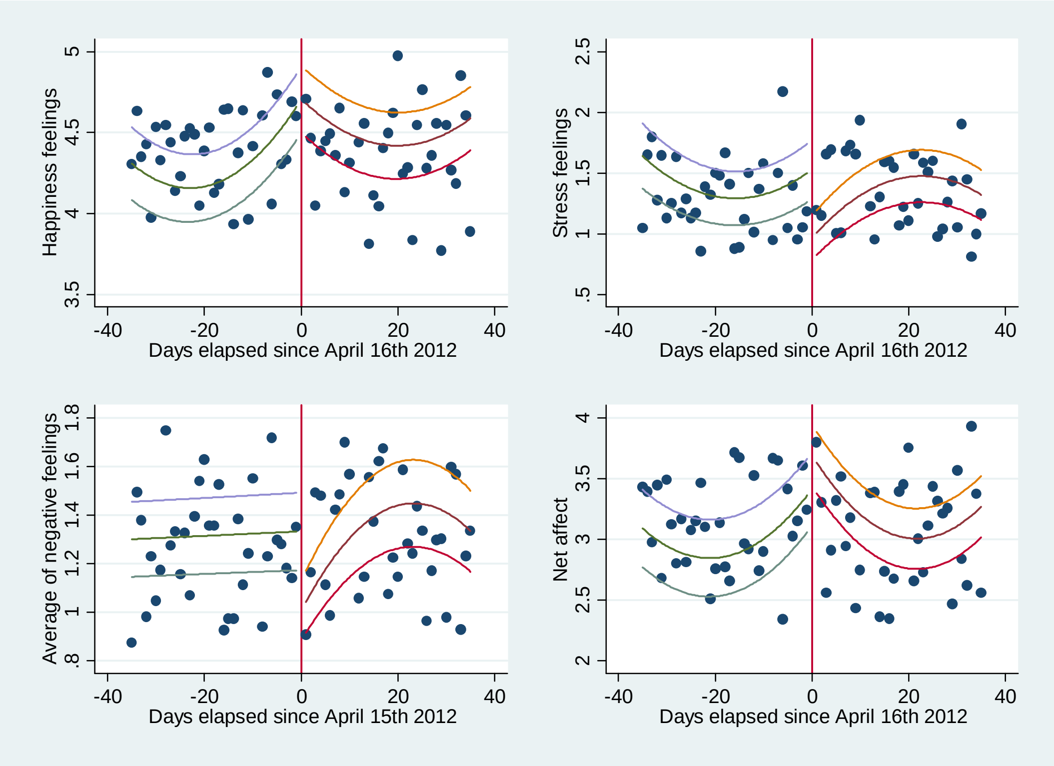
Note: The graphs plot the proportion of women in the sample, average age, the proportion of Blacks (versus Hispanics and other minority groups), and the average number of children of sample respondents, in each of the days elapsed before (negative values) or after (positive values) April 15th 2013, which corresponds to the day of the 2013 Boston marathon bombing. The dots correspond to the sample means each day. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week), as is standard in RDD. The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates. The graphs indicate that these explanatory variables are not discontinuous at the cut-off and therefore, the regression discontinuity design is valid.

Figure B4a – Outcome variables in the days before and after the 2013 Boston marathon, with a quadratic fit



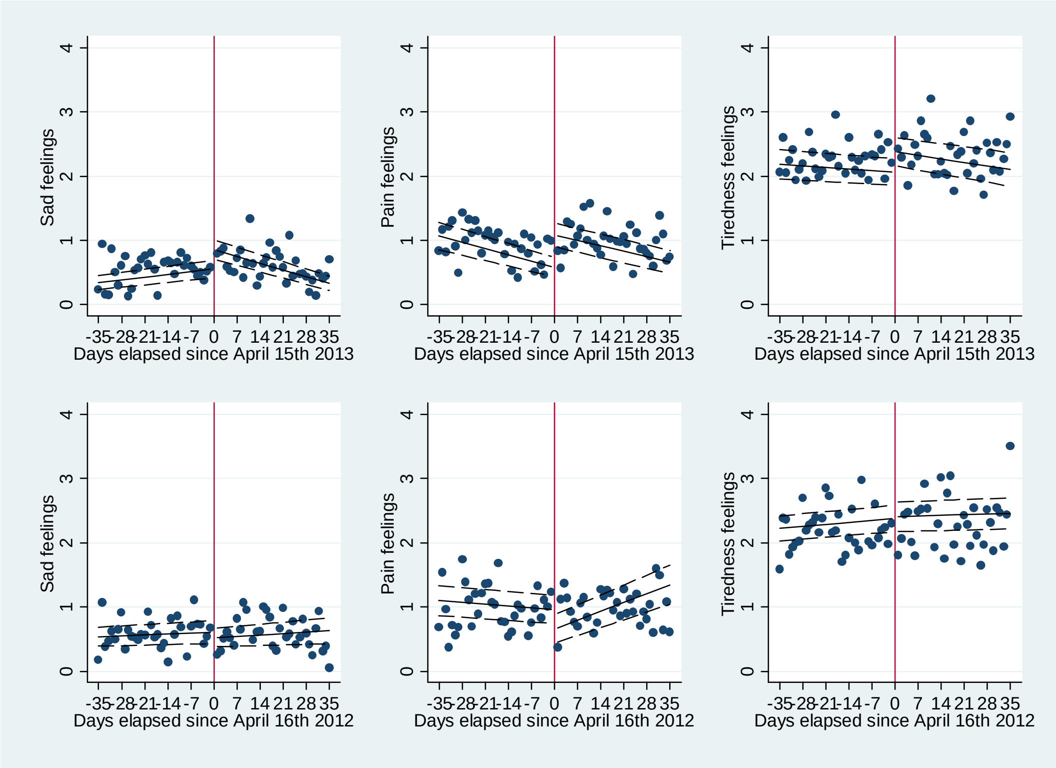
Note: The four graphs plot average happiness, average stress, average negative affect and net affect, in each of the days elapsed before (negative values) or after (positive values) April 15th 2013, which corresponds to the day of the 2013 Boston marathon bombing. The dots correspond to the sample means each day. The unbroken line shows the quadratic fit of triangular kernel estimates with a bandwidth of 35 days (without controlling for any explanatory variables, as is standard in RDD). The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Figure B4b – Outcome variables in the days before and after the 2012 Boston marathon, with a quadratic fit



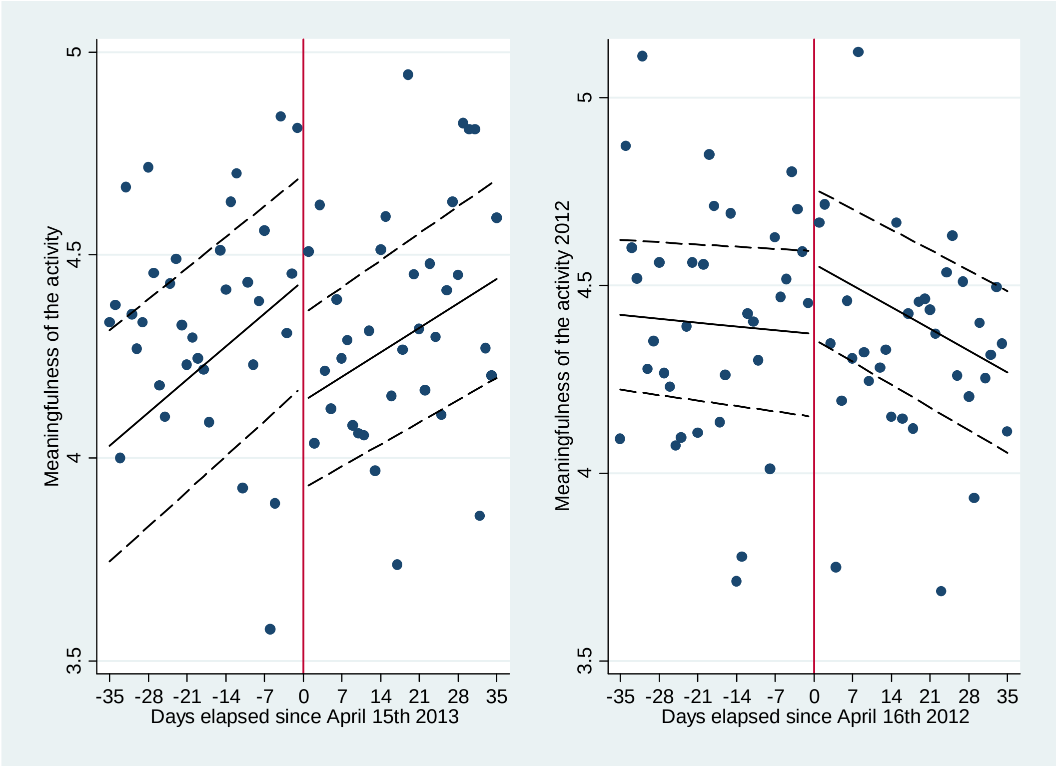
Note: The four graphs plot average happiness, average stress, average negative affect and net affect, in each of the days elapsed before (negative values) or after (positive values) April 16th 2012, which corresponds to the day of the 2012 Boston marathon, when there was no bombing. The dots correspond to the sample means. The unbroken line shows the quadratic fit of triangular kernel estimates with a bandwidth of 35 days (without controlling for any explanatory variables, as is standard in RDD). The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Figure B5 – Sadness, Tiredness, and Pain experienced in the days before and after the Boston marathon



Note: The vertical axis in the top panel shows average feelings of sadness, pain and tiredness (on a scale from 0 to 6) experienced in conjunction with performing three activities (selected randomly out of those reported in the diary) in the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero) in 2013. The bottom panel shows the average feelings of sadness, pain and tiredness (on a scale from 0 to 6) experienced in conjunction with performing three activities (selected randomly out of those reported in the diary) in the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero) in 2012. The dots correspond to the sample mean responses on each day. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week), as is standard in RDD. The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Figure B6 – Meaningfulness of the activity reported before and after the Boston marathon



Note: The left-hand graph plots average meaningfulness (on a scale from 0 to 6) reported for three activities (selected randomly out of those reported in the diary) in the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero) in 2013. The right-hand graph shows the average meaningfulness (on a scale from 0 to 6) reported for the three activities (selected randomly out of those reported in the diary) in the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero) in 2012. The dots correspond to the mean responses on each day. The unbroken line shows the linear fit of triangular kernel estimates with a bandwidth of 35 days, without controlling for any explanatory variables (not even the day of the week). The dashed lines are the 95 percent confidence intervals around the triangular kernel estimates.

Table B1– Full Results of Specification 3 of Table 2 RDD and Differences-in-Differences

	Happy	**Stress**	**Negative Affect**	**Net Affect**
Boston marathon 2013 (i.e. T * 2013)	-0.696***	0.691*	0.526**	-1.234***
	(0.246)	(0.379)	(0.200)	(0.341)
D* (1- T)* 2013	-0.000479	-0.00255	-0.00272	0.00381
	(0.00669)	(0.0121)	(0.00678)	(0.00989)
D* T* 2013	0.0190*	-0.0220	-0.0206***	0.0383***
	(0.00975)	(0.0147)	(0.00709)	(0.0130)
Boston marathon 2012 (i.e. T)	0.105	-0.219	-0.181	0.316
	(0.167)	(0.249)	(0.148)	(0.258)
D* (1-T)	0.00866*	-0.000783	0.000964	0.00599
	(0.00477)	(0.00943)	(0.00469)	(0.00843)
D* T	-0.00280	0.00805	0.00839*	-0.0106
	(0.00658)	(0.00754)	(0.00499)	(0.00905)
Monday	-0.150	0.387**	0.233**	-0.377**
	(0.0903)	(0.151)	(0.0932)	(0.150)
Tuesday	-0.122	0.444***	0.204**	-0.285**
	(0.0748)	(0.158)	(0.0782)	(0.123)
Wednesday	-0.148	0.431***	0.217***	-0.328**
	(0.0984)	(0.127)	(0.0821)	(0.146)
Thursday	-0.220**	0.487***	0.271**	-0.482***
	(0.0943)	(0.148)	(0.105)	(0.160)
Friday	-0.309***	0.272*	0.0927	-0.388**
	(0.106)	(0.138)	(0.120)	(0.162)
Saturday	0.0344	-0.0863	-0.0841	0.135
	(0.0550)	(0.107)	(0.0823)	(0.108)
Employed	0.0154	0.0709	-0.137*	0.147
	(0.0783)	(0.0847)	(0.072)	(0.127)
Dummy for no. dependent children	0.0276	-0.105	-0.0487	0.0451
	(0.118)	(0.101)	(0.0720)	(0.153)
No. of children	0.0725*	-0.0205	-0.0361	0.0973*
	(0.0428)	(0.0394)	(0.0262)	(0.0569)
Metropolitan area	0.0831	-0.00838	-0.0409	0.137
	(0.0989)	(0.0931)	(0.0649)	(0.134)
On holiday	0.1000	-0.112	-0.0227	0.141
	(0.180)	(0.218)	(0.185)	(0.103)
Woman	0.109	0.186***	0.129**	-0.0156
	(0.0794)	(0.0608)	(0.0545)	(0.108)
Age	-0.00916	0.0254**	0.0309***	-0.0384**
	(0.0119)	(0.0124)	(0.00920)	(0.0173)
Age squared	0.000161	-0.000326**	-0.000358***	0.000504***
	(0.000125)	(0.000127)	(9.66e-05)	(0.000181)
White	0.0382	-0.225	-0.152	0.200
	(0.109)	(0.191)	(0.129)	(0.187)
Black	0.224	-0.438**	-0.316**	0.575***
	(0.140)	(0.199)	(0.131)	(0.209)
Less than high school	0.119	-0.0670	0.105	0.0501
	(0.145)	(0.117)	(0.0822)	(0.190)
High school	0.0972	-0.259**	-0.0266	0.127
	(0.0898)	(0.109)	(0.0773)	(0.129)
College dropout	-0.0360	-0.0250	0.0394	-0.0779
	(0.103)	(0.0985)	(0.0577)	(0.131)
Log income	0.0136	-0.116**	-0.123***	0.131**
	(0.0410)	(0.0498)	(0.0295)	(0.0584)
2013	0.189	-0.225	-0.203*	0.407*
	(0.155)	(0.183)	(0.121)	(0.204)
Observations	4,366	4,396	4,341	4,316
R-squared	0.062	0.109	0.109	0.083

Note: T is a dummy equal to zero for respondents that answered the survey before the day of the Boston marathon and to one otherwise. Among the 2013 ATUS-WB respondents, T takes value zero for those that answered the survey before Monday April 15th, and value one otherwise. Among the 2012 ATUS WB respondents, T takes value zero for those that participated in the survey before Monday April 16th, and one otherwise. D denotes the number of days elapsed since T. Robust standard errors are in parentheses. Standard errors are clustered at the level of days elapsed. *** p<0.01, ** p<0.05, * p<0.1

Table B2 – The effect of the Boston marathon bombing on each individual outcome

	Mean month before	*Observations*	RDD-DD	Probits	Probit coefficient	Marginal effect
Happy, activity 1	4.48	4,493	-0.730**	Dummy =1	-0.447*	-0.177*
	(1.57)		(0.351)	if score >4	(0.243)	(0.0947)
Happy, activity 2	4.58	4,483	-0.914**	Dummy =1	-0.285	-0.112
	(1.47)		(0.355)	if score >4	(0.266)	(0.105)
Happy, activity 3	4.56	4,396	-0.379	Dummy =1	-0.362	-0.143
	(1.56)		(0.311)	if score >4	(0.266)	(0.105)
Stress, activity 1	1.44	4,510	-0.00453	Dummy =1	-0.143	-0.0559
	(1.85)		(0.521)	if score >1	(0.305)	(0.118)
Stress, activity 2	1.00	4,503	0.817**	Dummy =1	0.651**	0.244**
	(1.54)		(0.363)	if score >1	(0.310)	(0.117)
Stress, activity 3	1.02	4,409	1.240***	Dummy =1	0.734**	0.273**
	(1.53)		(0.380)	if score >1	(0.303)	(0.114)
Sad, activity 1	0.55	4,507	-0.00215	Dummy =1	0.185	0.0562
	(1.27)		(0.226)	if score >0.5	(0.262)	(0.0825)
Sad, activity 2	0.41	4,494	0.455**	Dummy =1	0.739**	0.218**
	(1.08)		(0.212)	if score >0.5	(0.314)	(0.102)
Sad, activity 3	0.43	4,396	0.469*	Dummy =1	0.544*	0.162
	(.14)		(0.260)	if score >0.5	(0.325)	(0.104)
Pain, activity 1	0.79	4,510	0.634*	Dummy =1	0.548**	0.203**
	(1.41)		(0.331)	if score >0.8	(0.252)	(0.0957)
Pain, activity 2	0.79	4,503	0.571**	Dummy =1	0.389	0.139
	(1.47)		(0.284)	if score >0.8	(0.056)	(0.0916)
Pain, activity 3	0.76	4,408	1.083**	Dummy =1	0.917***	0.337***
	(1.39)		(0.440)	if score >0.8	(0.271)	(0.101)
Tired, activity 1	2.13	4,508	0.973**	Dummy =1	0.742***	0.289***
	(1.95)		(0.382)	if score >2	(0.226)	(0.0836)
Tired, activity 2	2.15	4,498	-0.0649	Dummy =1	0.0795	0.0316
	(1.88)		(0.383)	if score >2	(0.268)	(0.106)
Tired, activity 3	2.06	4,402	-0.0604	Dummy =1	0.0269	0.0107
	(1.86)		(0.350)	if score >2	(0.214)	(0.0852)

Note: The binary outcomes are constructed by recoding the score as one when it takes value as noted and zero otherwise. Standard errors in parenthesis. Standard errors are clustered at the level of the running variable (days elapsed) in all models. Weights are applied. All models include other controls, see Equation 4 of Section 2. *** p<0.01, ** p<0.05, * p<0.1

Table B3a – The effect of the Boston marathon bombing on individual well-being. Binary (probit) outcomes

RDD and Diff-in-Diff (Eq 4), BW 35 days, 2012 & 2013	**Happiness**	**Stress**	**Negative Affect**	**Negative Affect**	**Negative Affect**	**Net Affect**	**Net Affect**	**Net Affect**
Mean month before	4.45	1.25	1.26	1.26	1.26	3.19	3.19	3.19
(st. dev)	(1.26)	(1.45)	(1.08)	(1.08)	(1.08)	(1.96)	(1.96)	(1.96)
	Dummy =1	Dummy =1	Dummy =1	Dummy =1	Dummy =1	Dummy =1	Dummy =1	Dummy =1
Probits	if score >4	if score >1	if score >1	if score >2	if score >3	if score >1	if score >2	if score >3
Probit estimate	-0.363	0.713**	0.816***	0.704**	0.151	-0.230	-0.506***	-0.679***
	(0.237)	(0.308)	(0.241)	(0.315)	(0.386)	0.227	(0.251)	(0.234)
Probit marginal effect	-0.141	0.278**	0.313***	0.200**	0.0140	-0.0566	-0.178*	-0.266***
	(0.0930)	(0.116)	(0.0849)	(0.102)	(0.0386)	(0.0586)	(0.0920)	(0.0876)
Observations	4,517	4,517	4,517	4,509	4,258	4,517	4,517	4,517

Note: The binary outcomes are constructed by recoding the score as one when it takes value as noted and zero otherwise. Standard errors are in parentheses. Standard errors are clustered at the level of the running variable (days elapsed) in all models. Weights are applied. All models include other controls, see Equation 4 of Section 2. *** p<0.01, ** p<0.05, * p<0.1

Table B3b – The effect of the Boston marathon bombing on individual well-being. Ordered probit models

RDD and Diff-in-Diff (Eq 4), BW 35 days, 2012 & 2013 data	**Happy**	**Stress**	**Negative Affect**	**Net Affect**
Mean month before	4.45	1.25	1.26	3.19
(standard deviation)	(1.26)	(1.45)	(1.08)	(1.96)
Ordered Probits	-0.593***	0.561**	0.607***	-0.713***
	(0.206)	(0.273)	(0.202)	(0.183)
Observations	4,366	4,396	4,341	4,316

Note: Standard errors are in parentheses. Standard errors are clustered at the level of the running variable (days elapsed) in all models. Weights are applied. All models include other controls, see Equation 4 of Section 2. *** p<0.01, ** p<0.05, * p<0.1

Table B4 – The effect of the Boston marathon bombing on individual well-being, dropping the largest US states.

RDD and Diff-in-Diff (Eq 4), BW 35 days, 2012 & 2013 data	**Happy**	**Stress**	**Negative Affect**	**Net Affect**
Dropping California (about 10% of sample	-0.734***	0.699*	0.504**	-1.262***
observations)	(0.266)	(0.371)	(0.195)	(0.357)
Observations	3,929	3,958	3,907	3,882
R-squared	0.066	0.131	0.123	0.095
Dropping New York state (about 5% of sample	-0.555**	0.560*	0.431**	-0.996***
observations)	(0.219)	(0.307)	(0.173)	(0.287)
Observations	4,169	4,194	4,140	4,120
R-squared	0.061	0.112	0.113	0.084
Dropping Florida (about	-0.875***	0.871**	0.635***	-1.521***
5% of sample observations)	(0.263)	(0.386)	(0.212)	(0.380)
Observations	4,114	4,142	4,089	4,066
R-squared	0.065	0.118	0.116	0.090

Notes: Robust standard errors in parentheses. Standard errors are clustered at the level of the running variable (days elapsed) in all models. Weights are applied. Models include other controls, see Equation 4 of Section 2.
*** p<0.01, ** p<0.05, * p<0.1

Table B5 – The effect of the Boston marathon bombing on individual well-being, setting placebo (fake) dates for the Boston marathon day.

RDD and Diff-in-Diff (Eq 4), BW 35 days, 2012 & 2013 data	**Happy**	**Stress**	**Negative Affect**	**Net Affect**
Setting the placebo attack on Monday 25th March 2013 &	0.149	0.0381	0.0484	0.140
its placebo counterfactual on Monday 26th March 2012	(0.295)	(0.310)	(0.223)	(0.400)
Observations	4,332	4,358	4,318	4,292
R-squared	0.076	0.110	0.143	0.114
Setting the placebo attack on Monday 1st April 2013 &	-0.209	0.149	0.147	-0.373
its placebo counterfactual on Monday 2nd April 2012	(0.270)	(0.343)	(0.246)	(0.458)
Observations	4,396	4,425	4,376	4,350
R-squared	0.057	0.100	0.097	0.070

Note: Robust standard errors in parentheses. Standard errors are clustered at the level of the running variable (days elapsed) in all models. Weights are applied. Models include other controls, see Equation 4 of Section 2. *** p<0.01, ** p<0.05, * p<0.1

Appendix C

Table C1 – Proportion of 2013 Boston Marathon Runners by US State

State	Percent	State	Percent
Alabama	0.5	Montana	0.2
Alaska	0.2	Nebraska	0.4
Arizona	1.2	Nevada	0.3
Arkansas	0.1	New Hampshire	1.8
California	8.6	New Jersey	2.4
Colorado	2.2	New Mexico	0.3
Connecticut	1.9	New York	6.6
Delaware	0.2	North Carolina	2.0
District Of Columbia	0.7	North Dakota	0.2
Florida	2.6	Ohio	3.0
Georgia	1.6	Oklahoma	0.4
Hawaii	0.2	Oregon	1.5
Idaho	0.4	Pennsylvania	3.9
Illinois	4.4	Rhode Island	0.7
Indiana	1.3	South Carolina	0.6
Iowa	0.7	South Dakota	0.1
Kansas	0.6	Tennessee	1.2
Kentucky	0.5	Texas	4.0
Louisiana	0.4	Utah	1.6
Maine	0.9	Vermont	0.4
Maryland	2.0	Virginia	2.8
Massachusetts	23.3	Washington	2.4
Michigan	2.5	West Virginia	0.2
Minnesota	2.3	Wisconsin	2.1
Mississippi	0.3	Wyoming	0.1
Missouri	1.0	Total from US	19,387

Table C2 – Proportion of 2013 Boston Marathon Runners by Country

Country	Percent
US	83
Canada	8
UK	1
Other 68 countries	8