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Evidence from the Boston Marathon Bombing

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

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Abstract

A growing literature concludes that terrorism impacts the economy, yet less is known about its impact on utility. This paper estimates the impact of the 2013 Boston Marathon Bombing on well-being, by exploiting representative U.S. daily data. Using both a regression discontinuity and an event study design, whereby the 2012 Boston marathon serves as a counterfactual, we find a sharp reduction in well-being, equivalent to a two percentage point rise in annual unemployment. The effect is stronger for women and those living in nearby States, but does not persist beyond one week, thus demonstrating the resilience of well-being to terrorism.

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. The economic consequences of terrorist acts on aggregate measures of national output, financial markets, foreign direct investment, and tourism have been well documented (Enders, Sandler, and Parise, 1992; Eckstein and Tsiddon, 2004; Gordon *et al.,* 2007; Abadie and Gardeazabal, 2008; Straetmans, Verschoor, and Wolff, 2008). However, less is known about the economic costs of terrorism at the individual level, particularly in terms of utility.

Terrorism may affect individuals by increasing feelings of uncertainty, fear, and risk aversion (Becker and Rubinstein, 2011), which are widely known to affect behaviour. 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, Garfin, and Cohen Silver, 2014) and affecting economic behaviour. This is in line with evidence from Israel showing that media coverage largely contributes to the impact of fatal attacks on consumer behaviour (Becker and Rubinstein, 2011). Terrorism may also increase feelings of stress, with spillovers on both adult and child health (Camacho, 2008; Pesko, 2014; Pesko and Baum, 2016). Thus, with the large-scale media coverage of terrorism, the well-being of individuals not directly involved in the attack 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), are associated with trauma related symptoms at the national level throughout the U.S.

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. This is the first study to estimate the impact of the bombing on well-being.[2] Not only may terrorist attacks not occur randomly (as terrorists, for example, often plan their action to have large media coverage)[3], it has also been shown that terrorism may impact individuals residing far away from the actual place of the attack (Metcalfe *et al.,* 2011). In this context, constructing a "synthetic" counterfactual using other U.S. States

[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).
[3] Attacks are often timed close to political elections (Montalvo, 2011), as a reaction to violence from the "other side" (Jaeger and Paserman, 2008), or due to specific trade relations (Mirza and Verdier, 2008).

may not be a valid empirical approach (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 in the Basque). Therefore, to account for the possible endogeneity of the day of the attack, as well as seasonality effects, we use answers to the ATUS survey around the Boston Marathon days in the previous year as a counterfactual, and implement a regression discontinuity design embedded within a differences-in-differences approach.

The Boston marathon bombing, (BMB hereafter), 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 family background. It was the first major terrorist act in the U.S. since the 9/11 attacks and, unlike previous terrorist acts which tended to target the business community, the BMB targeted 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 which lasted four days and involved a ‘shelter in place’ for one million Bostonians, door-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 BMB attack received intensive national and international media coverage and the event was on the New York Times front-page for eleven consecutive days. The 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 U.S. population administered between 2-4 weeks after the BMB, that repeated media exposure to the bombing was associated with higher stress across all U.S. 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.

The scant economic literature on the individual well-being effects of terrorism (e.g. Frey, Luechinger, and Stutzer, 2007; Krueger, 2007; Metcalfe, Powdthavee, and Dolan, 2011; Romanov, Zussman, and Zussman, 2012) use subjective well-being questions to approximate 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[4] 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 the U.S. Behavioural Risk Factor Surveillance System (BRFSS) and subjective well-being questions eliciting the number of days in the last month in poor mental health. Pesko (2014) also uses the BRFSS to examine the impact of the Oklahoma City bombing on stress and smoking using a regression discontinuity design, and Pesko and Baum (2016) use temporal distance from the 9/11 attacks as an instrument for stress.[5] Finally, two studies, both using the 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 a regression discontinuity design (Ford *et al.,* 2003; Knudsen *et al.,* 2005).[6] In general, this emerging body of work finds that terrorist attacks lead to a reduction in subjective well-being.

We add to this literature by using a more responsive measure of well-being which accounts for both positive and negative emotions associated with everyday activities. In particular, we analyse the effects of terrorism on "experienced" well-being using data derived from time diaries which are filled in daily by ATUS participants. These data contain unique measures of daily activities (Stancanelli, Donni, and Pollak, 2012; Hamermesh and Stancanelli, 2015) and emotional responses experienced during the day. The WB module solicits well-being across six emotional dimensions (asked in a randomised order) for three randomly selected activities reported by the respondent. This is referred to as 'experienced' well-being. While questions about satisfaction 'in general' or over the past few weeks can be powerful indicators of respondents' overall well-being, they may be subject to recall and cognitive biases (Kahneman *et al.,* 2004; Kahneman and Krueger, 2006; Dolan and Kahneman, 2008) and/or reflect expectations rather than actual life experiences (Schwartz, 1999). Measures of experienced well-being are more focused than these broader satisfaction questions based on longer time periods and without a direct connection to daily life activities (Kahneman *et al.,* 2004; Krueger and Mueller, 2012). Thus experienced well-being measures may be more suitable for analysing the impact of a significant event (such as a random terrorist act), as they

[4] 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 several different dimensions such as feeling of happiness and ability to concentrate.

[5] Brodeur (2016) also finds that terrorist attacks increase consumer pessimism regarding personal finances, business conditions, and buying conditions.

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

directly capture emotional responses to the event in real time (Kahneman *et al.,* 2004). Previous studies have relied on year-by-year and month-per-month (Metcalfe *et al.,* 2011) or week-by-week (Tsai and Venkataramani, 2015) comparisons, thus this study can provide a unique and more fine-grained analysis of changes in well-being due to terrorism.

Our findings indicate that the tragedy significantly affected individuals' experienced well-being. In particular, there is a reduction of one-third of a standard deviation in net affect, which represents the difference between the average of positive and negative emotions. The sharp drop in well-being is equivalent to the reduction in well-being associated with an increase of about two percentage points in the annual unemployment rate, according to our estimates. We also find that the effect of the bombing was stronger for women and for respondents living in States closer to the attack than those living further away. Finally, the impact of the attack appears to fade-out one week after the bombing, based on a combined event study[7] and differences-in-differences approach. The event study also reveals that experienced well-being during the baseline (pre-bombing) period is flat, as it should be, confirming the validity of our findings. The short-term impact of the attack on individual well-being is consistent with other studies examining the 9/11 attacks (e.g. Metcalfe *et al.,* 2011) and suggests that well-being may be resilient to terrorism.

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

1. The Data, Sample Selection, and Outcome Variables

The data are drawn 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).[8] A detailed description of the data is provided in Stone *et al.* (2016). Over ten thousand Americans are randomly drawn from a representative sample of the U.S. population to respond to this survey on a daily basis for a one-year period. Different respondents are included each day. The interviews take place continuously on all days of the week, beginning in January of each year and ending in

[7] Event studies are often used in applied finance to estimate abnormal returns after unexpected shocks (Sandler and Sandler, 2014).

[8] These data have been collected on a daily basis since 2010 and have previously been used to study the relationship between well-being and unemployment (Krueger and Mueller, 2012), income (Kushlev, Dunn, and Lucas, 2015), health (Schneider and Stone, 2014), family and work life (Flood and Genadek, 2016), and tiredness (Dolan and Kudrna, 2015).

December. The response rate to the survey is typically between 52 to 58 percent (depending on the year) and the BLS provides weights to correct for non-responses, which we use throughout the analysis. The day of the interview is usually chosen by the BLS interviewers and the ATUS activity diary collects information on the activities carried out over a 24-hour period, starting in the middle of the night. Activities have to be at least 5 minutes in duration to be included.

The well-being questions are derived from the WB module (see BLS (2014) and BLS (2015) and Appendix A for the exact questions). Three activities (from about 20) were randomly-selected from those reported by the respondent in the daily diary.[9] For each of these activities, respondents were asked to consider six emotional responses experienced while doing them: happy, sad, tired, pain, stress, and meaningful.[10] The order in which these responses were asked varied randomly. Each emotional response was measured on a scale from zero (not having experienced any happiness at all, for example) to six (having experienced the greatest happiness possible). Non-responses and refusals to reply are set equal to missing (there are very few out of many thousands of valid responses). We use the two positive emotions (happy and meaningful) to derive a measure of average positive affect, and the four negative emotions (sad, tired, pain and stress) to derive a measure of average negative effect. We also compute an overall measure of experienced well-being, so-called "net affect", given by the difference between the average of positive and negative affect. The reliability and validity of the experienced well-being questions within ATUS and WB has been established (see Lee *et al.,* 2016).

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) 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).

As the ATUS respondents are a random sample of the American Current Population Survey (CPS) survey, the ATUS and WB data were matched to the CPS data to obtain

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[9] With the exception of sleep, grooming and personal activities, which were not considered for inclusion.

[10] Meaningfulness has received wide attention by psychologists in relation to engagement/disengagement in employment (Kahn, 1990; May, Gilson, and Harter, 2004) and it may also respond to terrorism.

information on gender, age, education,[11] economic status,[12] family composition, race,[13] State of residence, and total household income.[14]

2. The Empirical Method

To control for the possible non-randomness of the day of the attack, we take a regression discontinuity design (RDD) approach combined with the differences-in-differences model using answers to the survey on the counterfactual day in the previous year to that of the attack to construct a plausible control group. Specifically, the day of the 2012 Boston marathon (Monday 16th April 2012) serves as a counterfactual for the actual day of the 2013 Boston marathon bombing (Monday 15th April 2013).

Differences-in-differences models have been widely used in the empirical literature on the economic costs of terrorism, although finding a counterfactual not affected by the attack is challenging. This has led some researchers to construct a "synthetic" counterfactual, drawn from data on unaffected geographical areas (e.g. Abadie and Gardeazabal, 2003). As show below, we find that residents in the rest of the U.S. also reacted to the terrorist attack which invalidates their use as a (synthetic) control group in our specific context (see Section 4).

An RDD approach, using the elapsed distance in days from the relevant event as the running variable (such as, for example, the individual's birthday, or a new law being passed) is an accepted procedure in the literature, as long as it cannot be manipulated by the individual (Lee and Lemieux, 2010). In our context, this involves testing whether the ATUS and WB survey was run continuously in the period of the attack. This can be checked using a McCrary test (McCrary, 2008); the results of which are presented in Figure B1 in Appendix B. The test shows that the survey was run continuously before and after the attack. As the BMB was an isolated attack, and we would not expect its impact to be long-lasting (Krueger, 2007), the RDD provides an estimate of the immediate effect of the attack (Angrist and Pischke, 2009; Lee and

[11] The educational variable is the original variable in the ATUS-CPS that ranges from 31 (corresponding to less than first grade) to 46 (indicating a doctoral degree), with 39 indicating a high school diploma and 43 a bachelor's degree. This is irrelevant here, as we are interested in data comparability in the control and treatment groups. In the regression model, we use education dummies.

[12] Economic status is a categorical variable including employed, unemployed, retired, and other economically inactive.

[13] We focus on White or Black, with the remaining group including Hispanics and other ethnic groups.

[14] Total household income is measured in sixteen brackets or intervals. Setting the respondent's household income equal to the lowest bound of the household income interval to which the respondent's household income is assigned (out of the 16 intervals available), produces a distribution of income with a median of $50,000, which is an underestimate of the 2013 median household income of $52,250 (according to Noss, 2014, for the U.S. Census Bureau). Alternatively, using the mid-point of each income bracket, as in the case of a uniform income distribution, would produce an overestimated median household income figure of $54,999. We use the logarithm of household income, which is less sensitive to measurement error.

Lemieux, 2010), while enabling us to control for the endogeneity of the day of the attack. This is an advantage relative to event studies which could also be applied in this context. In order for the RDD approach to be meaningful, we also require no other major change to have occurred on the day of the attack that may have affected the outcome. To control for this potential issue, we interact the RDD model with the differences-in-differences model that exploits the counterfactual calendar day.

Let us first write the differences-in-differences regression model for the outcome *W* (encompassing measures of experienced well-being) as:

1) $$W_i = \zeta\ T_i * Year_i + \tau\ T_i + \pi\ Z_i + \nu_{i} + \mu_{i}$$

where ζ reflects the effect of the attack on the outcome variable W. We have denoted the treatment 'T' as a dummy that takes value 1 in the days *after* the Boston marathon day in each year. The year of the attack is labelled Year and corresponds to 2013. Z is a matrix of individual characteristics, including controls for demographic characteristics (age, age-squared, race, and gender), education, economic status and household characteristics (number of people in households, number of children under age 18, and a quadratic in the logarithm of household income). We also control for whether the response day is a holiday and whether the respondent lives in a metropolitan area. We control for State, year, month, and day (Monday to Sunday) fixed effects in the matrix *ν*. The errors μ are assumed to be normally distributed. The standard errors are robust and clustered at the individual level (to control for the fact that emotional responses are considered for three activities). Individuals who answered the survey on the exact day of the actual or counterfactual attack (Monday April 16th in 2012 and Monday April 15th in 2013) are dropped from all the empirical estimations, as is standard practice in the field.

Regarding the RDD model, let the running variable be *D*, which is defined as the absolute distance in days from the terrorist attack; it is negative for the days before and positive for the days after, while the day of the actual or counterfactual attack is set as day zero (and dropped from the empirical model, as is standard). The treatment *T* is defined as above. The outcome variable *W* is observed either before the attack $W(_0)$ or after the attack $W(_1)$, and never at both times for the same individual. Let us assume, first, that any difference in outcomes between diaries recorded before or after that attack is due to the attack itself (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). For each individual *i*, interviewed before or after *T*, exposure to the treatment *T* is thus a deterministic function of the calendar day *J* for which the ATUS activity diary was recorded. We estimate the average impact (γ) of the attack on individual outcomes by taking the difference between the responses of individuals interviewed before or after the attack:

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

This can be approximated as usual under RDD by the difference in the mean outcomes of the respondents who filled out the ATUS diary in a window of days before and after the attack (the cutoff point). Assuming a linear model for the outcome and only selecting data for the year of the attack:

3) $$W_i = \gamma_{RD}\, T_i + \beta\, f(D_i)\, T_i + \lambda\, f(D_i)\, (1-T_i) + u_i$$

where f(D) is a polynomial function of the distance in days from the attack interacted with the treatment dummy *T*, to allow for different effects on either side of the cutoff. We apply the procedure in Calonico, Cattaneo, and Titiunik (2014) to determine the optimal bandwidth, and use the same bandwidth for the parametric and non-parametric models: 28 days.[15] Finally, to control for the possible non-randomness of the day of the attack, the RDD approach is combined with the differences-in-differences model using the pooled 2012 and 2013 data,[16] which gives our regression model as follows:

4) $$W_i = \zeta'\ T_i{*}Year_i + \varphi\, f(D_i){*}Year_i{*}T_i + \varphi'\, f(D_i){*}Year_i{*}(1-T_i) + \beta'\, f(D_i){*}T_i + \lambda'\, f(D_i){*}(1-T_i) + \pi'\, T_i + \tau'\, Z_i + \nu_i + \mu_i$$

In line with much of the empirical literature in this area (e.g. Holman *et al.,* 2014), we also conduct a separate analysis for respondents who were residents of States geographically close to the location of the attack and participants from all other States.[17] We expect that the well-being of residents from States closer to the event will be affected more, at least on average, than those in the rest of the U.S. Although in this case, given the cross-national and international nature of the marathon, one could hypothesize that everyone was likely to be affected in some way by the attack. Thus, this approach may underestimate the true effect of the attack. In particular, as shown in Appendix Table C1, only 23 percent of the marathon runners were from Massachusetts, and all U.S. States were represented in the race, with the largest being California

[15] Note that the optimal bandwidth varies depending on the sample used. The 4-week bandwidth was used in the main analysis as this corresponds to the pre-treatment sample (i.e. 2012).
[16] The direct and immediate impact of terrorism on individual well-being is modelled linearly, for simplicity, using an OLS regression and correcting the standard errors as appropriate.
[17] Note that it is not possible to analyse respondents from the Boston area separately due to sample size.

(8.6 percent), New York (6.6 percent), and Illinois (4.4 percent).[18] In addition, runners from over 70 different countries took part in the race. 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 define "States nearby" as the geographically-close States of Connecticut (1.9 percent), Maine (0.9 percent), New Hampshire (1.8 percent), New Jersey (2.4 percent), New York (6.6 percent), Pennsylvania (3.9 percent), Rhode Island (0.9 percent), Vermont (0.4 percent), as well as Massachusetts.

We also conduct a number of additional robustness tests for the main RDD differences-in-differences estimates including narrowing the bandwidth to two weeks and expanding it to six weeks to check the sensitivity of the estimates to setting different bandwidths, estimating the results without controlling for observable characteristics, estimating the results by including a quadratic for the running variable, and estimating RDD only models for 2012 and 2013. In particular, we estimate an event type model in order to test for the duration of the attack and to further investigate the flatness of the outcomes in our baseline period, which helps to validate the robustness of our conclusions (see Section 4).

3. Descriptive and Graphical Evidence

We first examine the comparability of the treatment and control samples before and after the BMB by producing a battery of t-tests. Next, we provide preliminary graphical evidence of the effect of the BMB on the outcome variables, as is customary in RDD.

3.1 Descriptive Statistics: Balance Tests for Treatment and Control Groups

In Table 1 we provide descriptive statistics for the treatment group in the 28 days *before* and *after* the day of the attack and for the control group in the 28 days *before* and *after* the *counterfactual day* of attack. The first part of the table provides *balance tests for treatment and control groups.* Column 2 shows that there are no statistically significant differences between the observables of the treatment group that answered the survey in the days *before* or the days *after* the BMB in terms of demographics or well-being scores. Columns 3 and 4 show that for the majority of measures, the 2012 *before* counterfactual group do not significantly differ from the 2013 *before* treatment group, and the 2012 *after* counterfactual group do not significantly differ from the 2013 *after* treatment group. There are more women in the *before* counterfactual

[18] While 83 percent of the race participants were residents of the U.S., residents from 70 other countries were represented in the race, the largest countries being Canada (8 percent) and the UK (1 percent).

group compared to the *before* treatment group and income is lower in the *after* counterfactual group compared to the *after* treatment group. The last part of Table 1 compares the *raw outcomes before and after the treatmen*t in the year of the bombing and the counterfactual year. The *after* counterfactual group have significantly higher net affect and lower negative affect compared to the *after* treatment group, which one would expect if the BMB were to have an impact on well-being.

[Insert Table 1 here]

3.2 Graphical RDD Evidence and the Common Trends Assumption

Next, we plot the raw data which show the average value of the positive and negative affect variables (grouped by bins of a day) in the 28 days *before* (negative values on the horizontal axis) or *after* (positive values) the day of the attack (set as zero). Non-parametric estimates of the effect of the attack on each outcome (the solid lines in the graphs) are also plotted together with the five percent confidence intervals around these estimates (the two dashed lines). The relevant "γ_{RD}" coefficients are estimated by means of a local polynomial with a triangular kernel (as in Nichols, 2014) for the optimal bandwidth (determined as in Calonico, Cattaneo, and Titiunik, 2014), using the BLS weights and correcting the standard errors as appropriate, however not including any controls. In addition, to corroborate our empirical strategy, we plot similar figures for the period around the counterfactual day of the attack (the right panel in Figure 1). This serves as a "placebo", and also as a test for the "common trends" assumption that the (predicted) outcome behaves similarly in the days *before* the true day of the attack (the baseline period), or the days *before* the counterfactual day of the attack.

[Insert Figure 1 here]

Figure 1 demonstrates a large immediate increase in respondents' negative affect in the aftermath of the BMB, both based on the raw data (the dots) and the RDD estimates (the solid lines). These negative effects of the bombing are statistically significant as the standard error bounds do not cross. We also plot comparable estimates for the counterfactual day of the attack in 2012 for which we detect a statistically significant decrease in negative affect. Thus, while Americans reported somewhat higher well-being after the 2012 marathon, possibly due to the positive emotions which large sporting events have been shown to generate (e.g. Kavetsos and Szymanski, 2010), after the 2013 marathon and the subsequent bombing, Americans reported lower well-being. This suggests that failing to use a counterfactual, and assuming that the bombing occurred on a random day (as was often done in earlier studies), may lead to an underestimate of the size of the BMB effect on well-being.

For positive affect, we observe a decrease in well-being after the bombing in the treatment period and an increase in well-being in the counterfactual period, although neither result is statistically significant. The baseline periods are very similar across the two sets of graphs, indicating that the common trend assumption is met.

4. Model Estimation Results

The main results of our estimation of the combined RDD differences-in-differences regressions (Equation 4) are presented in Table 2. Table 3 presents the results of a combined event study and differences-in-differences model to allow the effect of the bombing to vary in the four weeks following the tragedy, and also to test for effects in the four week baseline period preceding in the attack. Finally, Table 4 presents the results of the main RDD differences-in-differences model testing for heterogeneity in response to the attack by gender and geographical location.

4.1 Results of Estimation of Combined RDD and Differences-in-Differences

In Table 2 we only show the estimated coefficients for the impact of the attack on the three outcomes, but the full results are available on request. For simplicity, we use the same sample bandwidth in all specifications (28 days), which corresponds to the optimal bandwidth for the RDD (*Specification 1*), however we also check the robustness of the estimates to using 14 days (*Specification 2*) and 42 days (*Specification 3*) as is customary when implementing RDD. As further robustness, we also estimate the results by excluding the control variables and only including fixed effects for State, year, and day of the week (*Specification 4*), and including a quadratic (*Specification 5*).

[Insert Table 2 here]

As previous research has found that the impact of isolated terrorist attacks on the well-being of the general population are unlikely to last very long (Krueger, 2007), and due to the potential endogeneity of the day of the attack, using RDD combined with the counterfactual-calendar-day differences-in-differences approach appears appropriate to capture the immediate impact of the attack on well-being. *Specification 1* shows that the BMB is associated with a reduction in net affect, which is driven by an increase in negative affect. Regarding the size of the effects, the terrorist attack led to a significant reduction in net affect of -0.79, in absolute value, in the aftermath of the BMB, which corresponds to over a third of a standard deviation, and an increase in negative affect of 0.42, which also corresponds to over a third of a standard deviation.[19] To place this result in context, the estimated coefficient on being unemployed (as reported in the cross-sectional data and thus, not necessarily at the time of the lay-off) is equal to -1.1. Thus, the magnitude of a 0.79 well-being loss of one week for everyone is equivalent to the same well-being lose due to a rise in the annual unemployment rate by about two percentage points.[20]

As shown in *Specifications 2* and *3*, these estimates are largely robust to varying the bandwidth. In *Specification 2*, using a narrower bandwidth of 14 days, we find that the impact on net affect no longer reaches conventional levels of significance, however the effect for negative affect is larger and statistically significant. In *Specification 3*, using a wider bandwidth of 42 days, we replicate the findings from our main model in *Specification 1*, although the size of the effects are somewhat smaller, as is common in RDD studies as we are now further away from the cut-off. *Specification 4* shows that the results are robust to excluding observable characteristics and only including fixed effects for State, year, and day of the week, where we continue to observe a significant reduction in net affect and an increase in negative affect, with similar point estimates to *Specification 1*. In our final *Specification* (5), which includes a quadratic for the running variable, we find a half a standard deviation decrease in net affect, and a half a standard deviation increase in negative affect. Thus, while these results are larger, our main conclusions are not affected.

Overall, our findings are consistent with the theoretical and empirical literature which suggests that the occurrence of terrorism reduces well-being. Survey participants were not reminded of the BMB when responding to the survey. Thus, we would expect to find an effect only if the attack changed respondents' attitudes to daily life, as one may expect in the case of terrorism.

[19] The estimation results from separate models for each of the six individual emotions appear in Appendix D. These show that, on average, the BMB had no impact on positive emotions of happiness or meaningfulness, but the negative emotions of tiredness and pain significantly increased in the aftermath of the bombing.

[20] The estimated coefficient on unemployment is -1.1. Therefore, a one week decline in well-being of 0.79 is equivalent to 52 times Z per cent of individuals in the population being unemployed for one year. Therefore, Z is 0.79/(52*1.1)=0.014. Given that 63% of the U.S. population were active in the labour market in 2013, this equates to an equivalent drop in well-being of 2.2 percentage points.

4.2 Results of Estimation of Combined Event Study and Differences-in-Differences

In order to test how long these negative effects on experienced well-being persist, Table 3 presents the estimates of the differences-in-differences estimation which includes dummy variables for the four weeks *before* the BMB and the four weeks *after* the BMB for both the treatment and counterfactual periods. This also serves as an additional test of the robustness of the findings by providing estimates of the baseline period in the four weeks preceding the bombing. Across the three well-being measures, there are no statistically significant differences in the three weeks before the bombing, as expected, thus validating our approach. There is, however, a significant reduction in net affect (by one-third of a standard deviation), and a corresponding decrease in negative affect (by close to a third of a standard deviation), and an increase in positive affect (by one-quarter of a standard deviation) in the week after the bombing, although not in subsequent weeks. This suggests that the negative impacts of the BMB dissipated by week two. This finding may be driven by the heightened fear and national media coverage of the manhunt in the four day period after the attack. In sum, these results suggest that terrorist acts can have short term effects on experienced well-being, yet normal feelings subsequently resume, as found in other studies (e.g. Metcalfe *et al.,* 2011).

[Insert Table 3 here]

4.3 Heterogeneity in Responses

It is possible that different groups respond to terrorist acts in different ways. Therefore to explore heterogeneity in response to the attack we first conduct a sub-group analysis by gender, as women have often been found to be more risk-averse than men, though there is considerable disagreement on this in the empirical literature (Croson and Gneezy, 2009). We also conduct a sub-group analysis by residency, to examine whether residents of States geographically close to the place of the attack are affected differently from residents of States further away. Table 4 reports the results. *Specifications 1 and 2* show that the impact of the BMB on experienced well-being is restricted to women. Following the bombing, women experience a reduction in net affect, which is driven by a decrease in positive affect and an increase in negative affect. The size of the effects are larger than our baseline specification in Table 2, as net affect falls by two-thirds of a standard deviation, which is driven by a decline in positive affect by almost half a standard deviation and a rise in negative affect by more than half a standard deviation. There are no significant effects on men.

[Insert Table 4 here]

Specifications 3 and 4 present the estimates for respondents living in States near the bombing and States further away. A priori, one may expect the effects to be larger for those living closer to the event. Indeed, the results suggest large and statistically significant effects on the well-being of residents living geographically closer to the attack than those living further away. Specifically, residents in nearby States experience a significant reduction in both net affect and positive affect following the attack. The size of the effects are larger than in the base specification, with nearby States experiencing a fall in net affect of two-thirds of a standard deviation and a fall in positive affect of over one standard deviation. For States further away, the statistically significant results are restricted to an increase in negative affect by one-third of a standard deviation.

4.4 Robustness Checks

To examine the robustness of our approach, Table 5 reports the results of separate RDD analyses for 2012 (the counterfactual period) and 2013 (the treatment period). As expected, there are no significant differences in experienced well-being for the 2012 estimates, and the coefficients suggest higher well-being in the aftermath of the marathon. Conversely, for the treatment period (2013), the coefficients for net and negative affect are statistically significant and suggest lower well-being after the 2013 marathon and subsequent bombing. These results are largely consistent with the combined RDD difference-in-difference estimates, with a significant reduction in net affect and an increase in negative affect.

[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 found in a small number of earlier studies based on monthly or yearly data (e.g. Abadie and Gardeazabal, 2008, Metcalfe *et al.,* 2011). This study contributes to this literature by evaluating the impact of the Boston marathon bombing utilizing daily measures of well-being derived from unique diary data for a large (~10,000 respondents) and representative sample of the U.S. population drawn from the American Time Use Survey and Well-Being module.

We use a combined RDD differences-in-differences approach which allows us to eliminate potential confounding effects, such as changes in well-being that may be normal in the aftermath of a major sporting event, such as the Boston marathon which is attended by hundreds of thousands of spectators and is well-covered in the media. As well-being may vary by day of the week, month or season, and terrorist attacks may not occur on random days, we construct a counterfactual for the bombing using answers to the surveys around the days of the 2012 Boston marathon. It is important to note that the continuous nature of the ATUS data collection in the days surrounding the bombing ensures that the data were unrelated to the event and respondents were not reminded of the bombing during the interview. In addition, the randomised procedure which was used to select the activities during which well-being was measured, ensures that the activities most pertinent to the event, such as watching TV, were not necessarily given preference over others.

The use of measures of well-being that link emotional responses to a specific time point and/or activity is growing (Doyle *et al.,* 2017). As such, these measures may be less subject to framing effects compared to subjective or global measures which tend to reflect attitudes and expectations about one's life. Indeed, experienced and global assessments have been recognised as distinct constructs with different correlates. Experienced well-being measures are particularly suited for studying the immediate impact, if any, of unexpected and traumatic events. These data therefore provide a unique natural experiment on the effects of terrorism on the daily life of the average American.

In sum, we find that the BMB had a sharp negative impact on experienced well-being. Specifically, net affect, which is the difference between the average of positive and negative emotions, declined in the days after the event. The size of the effect of 0.79 points on a 0 to 6 point scale corresponds to a one-third of a standard deviation decrease. This represent a large reduction in well-being which is almost equivalent to the drop in well-being associated with an increase of roughly two percentage points in the annual unemployment rate. In addition, utilizing earlier ATUS and WB data, Stone *et al.* (2016) find that doubling income is associated with a 0.10 point reduction in sadness and a 0.20 point reduction in pain, but no effects on other emotions. These are far smaller than the 0.42 point increase in average negative affect found here. Our estimate is also larger than the 7 percent of a standard deviation decline found in Metcalfe *et al.* (2011), which is plausible considering that they studied the response of UK residents to the 9/11 attacks.

We find that women were particularly impacted by the event, having experienced both a reduction in positive emotions and an increase in negative emotions. This is consistent Metcalfe *et al.* (2011) who find that the 9/11 attacks reduced the subjective well-being of women in the UK, but not of men. It is also in-line with research which shows that women and men respond to stress in different ways due to both biological and psychological differences

(Bale and Epperson, 2015) and that women are more likely to experience post-traumatic stress disorders (Olff *et al*., 2007). While only a small proportion of respondents were likely to be directly affected by the bombing, previous studies have shown that those living in States not affected by the event (e.g. Schlenger *et al.,* 2002) and even in other countries (e.g. Metcalfe *et al.,* 2011) are negatively impacted by terrorist events, possibly due to media coverage, and also as some victims may reside in those States/countries. Indeed, we also confirm that those living in States closer to the bombing experienced significantly larger declines in well-being than those living in States further away, possibly due to the fear caused by the perpetrators being on the run in the days following the attack. However, our findings also confirm that terrorism can have effects beyond State boundaries and that the average American was impacted by the Boston marathon bombing.

Applying an event study approach combined with differences-in-differences, we conclude that the negative effects of the bombing had dissipated by the end of the first week. This result is in line with Krueger (2007) who finds that the 9/11 terrorist attack led to a decrease in enthusiasm and an increase in sadness for at least seven days after the attack, using similar experienced well-being data for Wisconsin. It is also consistent with Metcalfe *et al.* (2011) who, using monthly data only, identify no long-term impact of the 9/11 attack on subjective well-being in the U.K. 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 four week period preceding the Boston marathon, which corroborates our findings.

While the well-being effects of the Boston marathon bombing, as well as other isolated terrorist acts, do not appear to be long-lasting, thus suggesting the resilience of well-being to terrorism, there is evidence of a possible compounding effect (Holman *et al.,* 2014), such that repeated media exposure to multiple terrorist attacks may lead to an increase in long-term stress and trauma-related disorders. This suggests that the increasing frequency, and thus reporting, of terrorist acts in Europe and the U.S may potentially contribute to higher levels of stress-related diseases in the long term. It is also possible that feelings of fear and risk aversion, which are generated by the uncertainty of terrorist events (Becker and Rubinstein, 2011) and are known to effect economic decisions, will lead to a decline in economic activity. Thus, 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 act as protective factors against the negative long-term consequences of terrorism on well-being.

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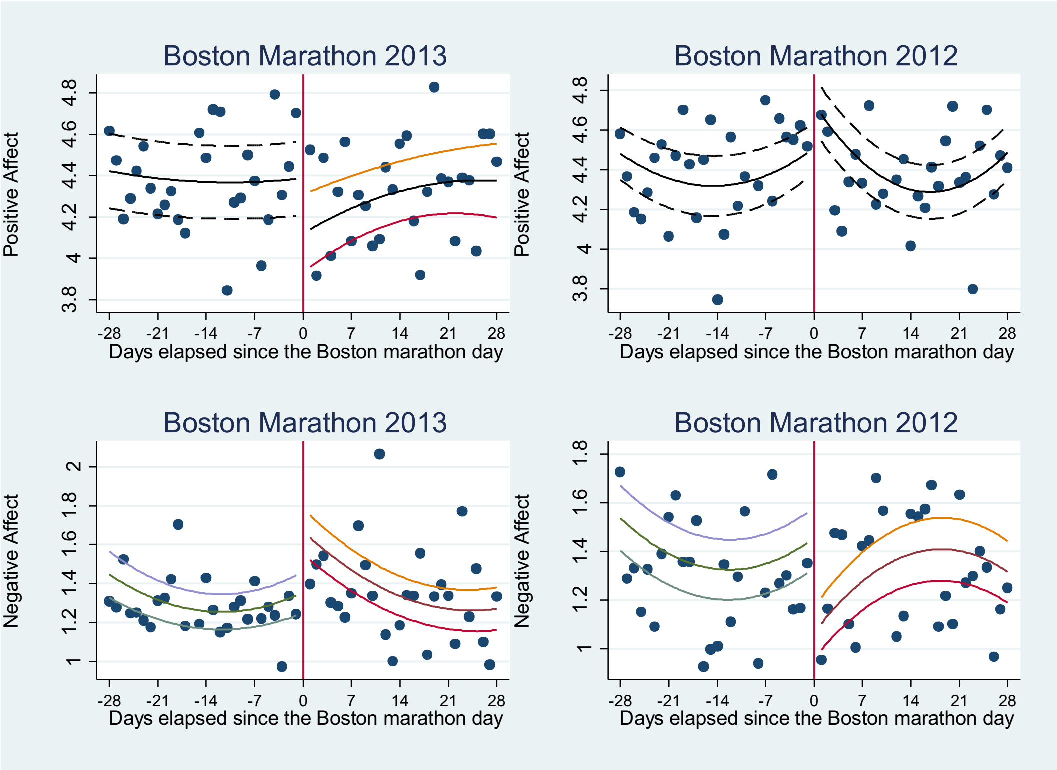
Figure 1 – Experienced Well-being Before and After the Boston Marathon Day



Note: The vertical axis in the top panel shows the average positive affect (on a scale from 0 to 6) in the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero) in 2013 (left-hand side) and 2012 (right-hand side). The bottom panel shows the analogous negative affect. The dots correspond to the raw averages by bins of one day. The solid line is fitted non-parametrically using a triangle kernel with a bandwidth of 28 days. The dashed lines are the 5 percent confidence intervals around the triangular kernel estimates.

Table 1 – Sample Descriptive Statistics Before and After the Boston Marathon day

	Boston marathon, Monday 15th April 2013		**Boston marathon, Monday 16th April 2012**	
	1-28 days before	**1-28 days after**	**1-28 days before**	**1-28 days after**
Age	48.14 (0.32)	47.68 (0.33)	48.21 (0.31)	48.70 (0.31)
Woman	0.54 (0.01)	0.54 (0.01)	**0.57 (0.01)**	0.54 (0.01)
Education	40.49 (0.05)	40.45 (0.05)	40.47 (0.05)	40.33 (0.05)
White	0.80 (0.01)	0.80 (0.01)	0.78 (0.01)	0.81 (0.01)
Black	0.15 (0.01)	0.14 (0.01)	0.14 (0.01)	0.13 (0.01)
Income	59596 (765)	59665 (831)	58718 (768)	**57397 (776)**
Observations	*956*	*966*	*985*	*1060*
Work hours	5.35 (4.18)	5.69 (4.07)	5.39 (4.42)	5.63 (.4.48)
Observations	*560*	*576*	*574*	*600*
Employed	0.59 (0.49)	0.61 (0.49)	0.59 (0.49)	0.60 (0.49)
Observations	*956*	*966*	*985*	*1060*
Net Affect	3.09 (2.07)	2.90 (2.12)	3.00 (2.05)	**3.09 (2.03)**
Observations	*2653*	*2602*	*2724*	*2839*
Positive Affect	4.39 (1.43)	4.29 (1.49)	4.38 (1.44)	4.40 (1.40)
Observations	*2666*	*2617*	*2731*	*2857*
Negative Affect	1.31 (1.18)	1.39 (1.21)	1.38 (1.15)	**1.31 (1.20)**
Observations	*2683*	*2643*	*2759*	*2867*

Notes: The figures are means with standard deviations in parentheses. Bold numbers in Column 2 indicate a statistically-significant mean difference between the 2013 "before" and "after" samples. Bold numbers in Column 3 indicate a statistically-significant mean difference between the 2012 "before" and the 2013 "before" samples. Bold numbers in Column 4 indicate a statistically-significant mean difference between the 2012 "after" and the 2013 "after" samples. The observations are weighted using ATUS WB weights. Emotional responses are measured on a scale of 0 to 6.

Table 2 – The Effect of the Boston Marathon Bombing on Experienced Well-being

	Net Affect	Positive Affect	Negative Affect
Mean 28 days before (standard deviation)	3.09 (2.07)	4.39 (1.43)	1.31 (1.18)
1) RDD*2013	-0.793	-0.375	0.420
Optimal bandwidth (28 days), controls 1	(0.373)	(0.259)	(0.203)
Observations	10,818	10,871	10,952
R-squared	0.077	0.087	0.070
2) RDD*2013	-0.773	-0.322	0.521
14 days bandwidth, controls 1	(0.539)	(0.370)	(0.278)
Observations	5,658	5,686	5,737
R-squared	0.086	0.108	0.091
3) RDD*2013	-0.635	-0.310	0.318
42 days bandwidth, controls 1	(0.313)	(0.216)	(0.177)
Observations	14,954	15,024	15,131
R-squared	0.059	0.071	0.052
4) RDD*2013	-0.814	-0.327	0.485
Optimal bandwidth (28 days), controls 2	(0.384)	(0.276)	(0.209)
Observations	10,818	10,871	10,952
R-squared	0.056	0.048	0.046
5) RDD*2013	-1.171	-0.499	0.688
Optimal bandwidth (28 days), quadratic, controls 1	(0.604)	(0.407)	(0.319)
Observations	10,818	10,871	10,952
R-squared	0.079	0.088	0.072

Notes: RDD*2013 are regression discontinuity estimates combined with differences-in-differences. Robust standard errors in parentheses. Standard errors are clustered at the individual level. Weights applied. The optimal bandwidth is 28 days. The models include linear controls for the days elapsed before or after the attack and their interaction with the day of the attack, as standard, and these are also fully interacted with the year of the attack. Controls 1: gender, a quadratic in age, education dummies, race dummies, number of children aged less than 18, number of other adults, a quadratic in the logarithm of household income, a series of main economic activity dummies (employment, unemployment, retirement, other inactivity), a dummy for residing in a metropolitan area, an indicator for whether the day of the interview was a vacation day, and State, day, and year fixed effects. Controls 2: fixed effects for State, day, and year only. Emotional responses are measured on a scale of 0 to 6.

Table 3 – Duration of the Effect the Boston Marathon Bombing on Experienced Well-being

	Net Affect	**Positive Affect**	**Negative Affect**
One-week after			
*2013	-0.729	-0.369	0.359
	(0.272)	(0.190)	(0.143)
Two-weeks			
after*2013	-0.182	-0.0587	0.0827
	(0.238)	(0.162)	(0.146)
Three-weeks			
after*2013	0.365	0.142	-0.202
	(0.237)	(0.154)	(0.153)
Four-weeks			
after*2013	0.0691	0.0211	-0.0523
	(0.260)	(0.185)	(0.131)
Two-weeks			
before*2013	0.258	0.231	-0.0277
	(0.270)	(0.195)	(0.154)
Three-weeks			
before*2013	-0.0393	-0.0815	-0.0385
	(0.272)	(0.195)	(0.155)
Four-weeks			
before*2013	0.00636	-0.0483	-0.0367
	(0.274)	(0.170)	(0.159)
Observations	10,818	10,871	10,952
R-squared	0.080	0.089	0.072

Notes: Event-study differences-in-differences model, using the 2012 Boston marathon day as a counterfactual. The week before the marathon (in either 2012 or 2013) is the reference period. Robust standard errors in parentheses. Standard errors are clustered at the individual level. Weights applied. The models also include dummies for the weeks before and after the 2012 Boston marathon. Controls: gender, a quadratic in age, education dummies, race dummies, number of children aged less than 18, a quadratic in the logarithm of household income, a series of main economic activity dummies (employment, unemployment, retirement, other inactivity), a dummy for residing in a metropolitan area, an indicator for whether the day of the interview was a vacation day, and State, day, and year fixed effects. Emotional responses are measured on a scale of 0 to 6.

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

	Net Affect	Positive Affect	Negative Affect
Mean (standard deviation) 28 days before – women	3.13 (2.1)	4.51 (1.4)	1.39 (1.3)
Mean (standard deviation) 28 days before – men	3.05 (2.0)	4.28 (1.5)	1.24 (1.1)
Mean (standard deviation) 28 days before - States nearby	2.99 (1.96)	4.40 (1.3)	1.41 (1.1)
Mean (standard deviation) 28 days before - other States	3.11 (2.09)	4.39 (1.5)	1.29 (1.2)
1) RDD*2013, women only	-1.423	-0.649	0.763
Optimal bandwidth, controls 1	(0.500)	(0.323)	(0.275)
Observations	6,006	6,034	6,068
R-squared	0.105	0.113	0.088
2) RDD*2013, men only	-0.0592	-0.0437	0.0350
Optimal bandwidth, controls 1	(0.518)	(0.370)	(0.270)
Observations	4,812	4,837	4,884
R-squared	0.108	0.111	0.121
3) RDD*2013, States nearby only	-1.346	-1.537	-0.162
Optimal bandwidth (28 days), controls 1	(0.752)	(0.495)	(0.422)
Observations	1,801	1,809	1,830
R-squared	0.282	0.234	0.223
4) RDD*2013, other States only	-0.391	0.0568	0.447
Optimal bandwidth (28 days), controls 1	(0.377)	(0.267)	(0.219)
Observations	9,017	9,062	9,122
R-squared	0.063	0.083	0.068

Notes: RDD*2013 are regression discontinuity estimates combined with differences-in-differences. Robust standard errors in parentheses. Standard errors are clustered at the individual level. Weights applied. The optimal bandwidth is 28 days. We consider States nearby as Boston, Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey and Pennsylvania. The RDD models include linear controls for the days elapsed before or after the attack and their interaction with the day of the attack, as standard, and these are also fully interacted with the year of the attack. Controls 1: a quadratic in age, education dummies, race dummies, number of children aged less than 18, a quadratic in the logarithm of household income, a series of main economic activity dummies (employment, unemployment, retirement, other inactivity), a dummy for residing in a metropolitan area, an indicator for whether the day of the interview was a vacation day, and State, day, and year fixed effects. Emotional responses are measured on a scale of 0 to 6.

Table 5 – Effect of the 2013 or 2012 Boston Marathon Bombing on Experienced Well-being

	Net Affect	**Positive Affect**	**Negative Affect**
Boston Marathon 2013			
1) RDD	-0.561	-0.195	0.373
Optimal bandwidth (28 days), controls 1	(0.254)	(0.179)	(0.137)
Observations	5,563	5,588	5,626
R-squared	0.104	0.108	0.121
Boston Marathon 2012			
2) RDD	0.334	0.121	-0.210
Optimal bandwidth (28 days), controls 1	(0.253)	(0.166)	(0.149)
Observations	5,255	5,283	5,326
R-squared	0.128	0.128	0.106

Notes: RDD are regression discontinuity estimates. Robust standard errors in parentheses. Standard errors are clustered at the individual level. Weights applied. The optimal bandwidth is 28 days. The models include linear controls for the days elapsed before or after the attack and their interaction with the day of the attack, as standard. Controls 1: gender, a quadratic in age, education dummies, race dummies, number of children aged less than 18, number of other adults, a quadratic in the logarithm of household income, a series of main economic activity dummies (employment, unemployment, retirement, other inactivity), a dummy for residing in a metropolitan area, an indicator for whether the day of the interview was a vacation day, and State, day, and year fixed effects. Emotional responses are measured on a scale of 0 to 6.

Appendix A

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.

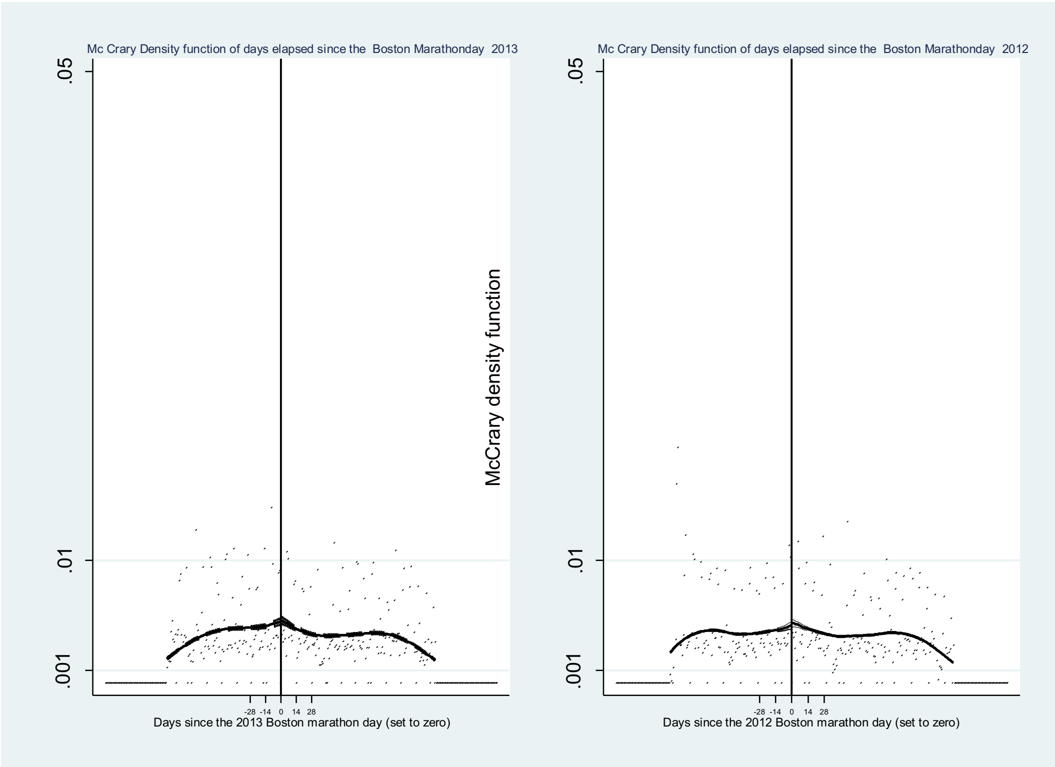
1.	Happy	First, from 0 – 6, where a 0 means you were not happy at all and a 6 means you were very happy, how happy did you feel during this time?
2.	Tired	From 0 – 6, where a 0 means you were not tired at all and a 6 means you were very tired, how tired did you feel during this time?
3.	Stressed	From 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?

6.	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.

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

Appendix B

Figure B1 – McCrary density function of daily responses to the ATUS-WB survey



The vertical axis shows the McCrary density of the running variable (days elapsed since the Boston marathon) by the days before (negative values) or after (positive values) the Boston marathon day (set equal to day zero), in 2013 (left panel) and 2012 (right panel). The dots correspond to the raw averages by bins of one day. The solid line is non-parametrically fitted using a triangle kernel with a bandwidth of 140 days. The dashed lines are the 5-percent confidence intervals around the triangular kernel estimates. The corresponding McCrary test validates our empirical strategy (the test statistics are 1.085 for the 2013 data, and 0.72 for the 2012 data).

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

Appendix D

Table D1 – The effect of the 2013 Boston Marathon Bombing on the Individual Well-being Measures

	Happy	Meaning	Stress	Sad	Tired	Pain
1) RDD*2013						
Optimal bandwidth, controls 1	-0.456	-0.304	0.0823	0.243	0.761	0.592
	(0.298)	(0.297)	(0.319)	(0.219)	(0.332)	(0.284)
Observations	*10,980*	*10,912*	*11,022*	*11,003*	*11,012*	*11,020*
R-squared	0.066	0.080	0.078	0.053	0.069	0.110

Notes: RDD*2013 are regression-discontinuity estimates combined with differences in differences. Robust standard errors in parentheses. Standard errors are clustered at the individual level. Weights applied. The optimal bandwidth is 28 days. The models include linear controls for the days elapsed before or after the attack and their interaction with the day of the attack, as standard, and these are also fully interacted with the year of the attack. Controls 1: gender, a quadratic in age, education dummies, race dummies, number of children aged less than 18, number of other adults, a quadratic in the logarithm of household income, a series of main economic activity dummies (employment, unemployment, retirement, other inactivity), a dummy for residing in a metropolitan area, an indicator for whether the day of the interview was a vacation day, and State, day, and year fixed effects. Emotional responses are measured on a scale of 0 to 6.

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