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Well-being Effects of Extreme Weather Events in the United States

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Abstract

The increase in weather and climate disasters in recent years has prompted an interest in analyzing their consequences and required mitigation and adaptation measures to minimize their potentially large impacts on individuals' welfare. We match forty-two billion-dollar disasters with individual survey data from the Behavioral Risk Factor Surveillance System between 2005 and 2010 to estimate the effect of extreme weather events on the subjective well-being of U.S. residents. Our results indicate that natural disasters have a negative and robust impact on subjective well-being in the affected communities, and that this impact decays over time, disappearing on average 6 to 8 months after the event. Severe storms are the main culprit in the reduction of individual life satisfaction in our sample. We then investigate the attenuating impact of health care access, natural-peril insurance, and governmental assistance programs and find a partial compensating role for both private and public protective measures.

Keywords: Subjective well-being, extreme weather, disasters, climate change, mental health.

JEL: Q54, I31, I38

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1. Introduction

The interest of economists in studying the impacts of natural disasters on human well-being is not new but has intensified in recent years due to an increase in their incidence and damages. Between 2005 and 2014 the global disaster database EM-DAT recorded an annual average of 380 natural disasters worldwide caused by earthquakes, tsunamis, volcanic eruptions, hurricanes, floods and droughts (among others), which claimed almost 76,500 lives and affected 199.2 million people on average each year. Of these natural disasters, 335 (or 88%) were climate-related, an increase of 14% from the previous decadal average (CRED and UNISDR 2015). Weather and climate disaster

time series from 1980-2011 in the U.S. also suggest increasing trends in both the annual frequency and aggregate losses of “billion-dollar” disasters (Smith and Katz 2013), with climate change expected to further increase the frequency, intensity, and duration of extreme weather events (IPCC 2013). In 2017 there were 16 billion-dollar disasters in the U.S. including three hurricanes –Harvey, Irma and Maria- with combined damages estimated at a record \$306.2 billion (NCEI 2017).

In addition to more prevalent natural hazards, the concentration of population and physical structures in hazardous areas contributes to larger impacts of disasters on human well-being. Some impacts, such as the financial losses associated with property damages and the fiscal consequences of reconstruction, are tangible and can be easily quantified. However, natural disasters can also cause stress and other psychological costs (uncertainty, grief for the bereaved, individual and collective traumas) (Carroll et al. 2009, Luechinger and Raschky 2009). These intangible costs are clearly very important but are unaccounted for in official economic estimates of disaster damages.¹

Psychologists recognize the need for immediate mental health aid after natural disasters. Public health scientists hypothesize a direct link between acute weather disasters and mental health by exposing people to trauma, and an indirect link by affecting physical health and community well-being (Berry et al. 2010). Regarding the direct link, most prior studies focus on whether the individual experienced the disaster-related traumatic events or stressors and if she has post-traumatic stress disorder (PTSD), which is the central psychopathology in the aftermath of

¹ For example, the loss estimates in the billion-dollar weather and climate disasters published by the U.S. National Centers for Environmental Information (NCEI) include both insured and uninsured losses in the following categories: physical damage to residential, commercial and government/municipal buildings, material assets within a building, time element losses, vehicles, public and private infrastructure, and agricultural assets (e.g., buildings, machinery, livestock). Disaster loss assessments do not take into account losses to natural capital/assets, healthcare related losses, values associated with loss of life, or other psychic costs.

disasters (Norris et al. 2002, Galea et al. 2005, Lowe et al. 2005, Neria et al. 2008, Fergusson et al. 2014).² In their review of 116 studies from 40 natural disasters between 1963 and 2005, Neria et al. (2008) concluded that the prevalence of PTSD in affected communities in the first 1-2 years after natural disasters ranges from 0.7% to 60% depending on the degree of exposure (Canino et al. 1990, Najarian et al. 1996). However, it is difficult to quantify the economic significance of these findings. Moreover, the effects of a disaster on the subjective well-being of individuals in affected communities go beyond those to the directly impacted. They include the impacts to their friends, relatives, first responders all the way to individuals experiencing distress after seeing or hearing media reports (Cohen 2002).

Economists have traditionally used stated and revealed preference methods to estimate the welfare loss associated with extreme weather events. In stated preference studies, survey respondents are asked directly for their willingness to pay to reduce hazard risks, e.g. flood (Brouwer et al. 2009, Botzen et al. 2009) or wildfire risks (Loomis et al. 2009, Calkin et. al 2013). Revealed preference methods, on the other hand, rely on market transactions to derive the implicit value of reducing hazard risks. A number of studies have used hedonic property price functions to estimate the effects of different natural hazards on residential property values; for example, floods (Bin and Polasky 2004, Bin and Landry 2013, Atreya et al. 2013); hurricanes and tropical cyclones (Hallstrom and Smith 2005, Simmons et al. 2002), and wildfires (Loomis 2004, Donovan et al. 2007). While stated preference methods might capture some of the less tangible costs of disasters if the hypothetical scenario highlights their psychological costs, it is not clear to what extent revealed preference methods can capture these effects, particularly on those indirectly affected.

² According to Lowe et al. (2005) disaster related traumatic events include (a) the individual being injured, (b) a close friend or family member being injured, and (c) a close friend or family member being killed, each as a direct result of the disaster or its aftermath. Disaster-related stressors include (a) being displaced for over a week, (b) going without electricity, heat or water for over a week, (c) damage to the home, and (d) income losses due to the disaster.

In this paper, we use a different approach that is arguably better suited to quantify the effects of weather disasters on well-being; we directly estimate their impact on an indicator of global satisfaction with life as a measure of subjective well-being (SWB). For this, we merge individual-level survey data from the Behavioral Risk Factor Surveillance System (BRFSS), with the storm events and the billion-dollar disaster events databases of the National Center for Environmental Information (NCEI).

Recent years have seen economists increasingly use data on SWB to study the impact of economic and social factors (such as income and unemployment), institutions and public goods or bads – in particular environmental quality - on human welfare (for reviews see e.g., Frey and Stutzer 2002, Dolan et al. 2008, MacKerron 2012, Welsch and Ferreira 2013). Life satisfaction is a relatively stable measure of experienced utility that blends a cognitive assessment of quality of life as a whole but that is also sensitive to transitory factors. The evaluation of the impacts of natural disasters on human well-being is a particularly suitable application of SWB data.

Luechinger and Raschky (2009) use SWB data to measure the utility consequences of flooding in 16 European countries between 1973 and 1998 and find a significant and robust negative impact on SWB, which translates into a willingness to pay of 23.7 percent of household annual income for preventing a flood disaster. von Möllendorff and Hirschfeld (2016) also show a significant negative effect on SWB of storm and hail events and floods in affected regions in Germany. Additional studies have estimated the effect on SWB of wildfires in four Mediterranean European countries (Kountouris and Remoundou 2011), and of droughts in Australia (Carroll et al. 2009). Rehdanz et al. (2015) find significant well-being effects of the combined earthquake, tsunami and nuclear accident in eastern Japan in 2011 that are proportional to proximity to the Fukushima site, and up to 72 percent of annual household income.

Unlike previous studies that have focused on a specific disaster or disaster type, we contrast and compare the effect of different types of extreme weather events, including tropical cyclones (mainly hurricanes), severe storms (mainly tornadoes), flooding, drought, wildfire and freeze, on the SWB of U.S. residents from 2005 to 2010. It is well known that risk perceptions depend on the type of underlying hazard. For example, Viscusi (2009) shows that the value of a statistical life can be different based on the cause of damages and individual's perceived risk of damages.

The focus on the U.S. is also new. Because of its geography, climate and size, the U.S. consistently ranks among the top disaster-prone nations, making it an especially appropriate setting for this research. For example, in 2015 it was the second country most affected by natural disasters, with 22 reported disasters, behind China with 26 (UNISDR 2015). During the period covered by our analysis, 2004-2010, there were ten tropical cyclones, seventeen severe storms and tornados, four floods, five droughts, two freezes and four wildfires classified as billion-dollar disasters by the U.S. NCEI (Appendix table 1). In addition, although the U.S. is a large country, by analyzing SWB data of only one country, we mitigate problems of intercultural comparability of responses to SWB questions in multinational studies (Eid and Diener 2001) and cross-cultural differences in risk perceptions of disasters (Gierlach et al. 2010).

The BRFSS records the exact date of the interview, allowing us to match interview and disaster dates to explore the temporal decay of the impacts of natural disasters on SWB. We find that disasters (and among the different types of disasters, severe storms especially) have the largest negative effect on SWB within the first six months after their occurrence and that their impact decays with time. Interestingly, considering a longer time frame of 18 months used in previous studies would lead to underestimating the welfare losses of disasters in our study.

Individuals can purchase insurance to protect against the financial losses of disasters. There

are also government programs that provide financial assistance after a disaster. For the two risk transfer mechanisms for which we have data: flood insurance and health insurance, and for several governmental assistance programs, we present suggestive evidence that they help mitigate the negative impacts of disasters on SWB.

The rest of the paper proceeds as follows: Section 2 describes the data used in the analysis; Section 3 presents the quasi-experimental design to identify the impact of disasters on SWB and the econometric models. Section 4 contains the main estimation results and robustness checks. Section 5 presents additional analyses on the role of public and private risk transfer mechanisms to mitigate disaster impacts, and on the effect of disasters on alternative indicators of SWB. Section 6 concludes.

2. Data

Individual level data comprising SWB scores and socio-demographic information (age, education, income, marital status, employment status, health status, sex) come from the BRFSS, which is a state-based health survey conducted annually by the Centers for Disease Control and Prevention (CDC) to gather information on major behavioral risks among adults associated with premature morbidity and mortality. Data are collected for all 50 U.S. states. Between 2005 and 2010 the questionnaire contained a standard 4-point scale life satisfaction question that we use as a measure of SWB: “In general, how satisfied you are with your life?” Respondents could choose between the following categories: “very satisfied”, “satisfied”, “dissatisfied” or “very dissatisfied”. The average life satisfaction in the sample is 3.4, between “satisfied” and “very satisfied.” Table 1 presents summary statistics of the life satisfaction question and other individual socio-demographic controls included in the regressions.

[Table 1 about here]

In addition to the state, the BRFSS records the county of residence of the respondents. BRFSS does not collect information on whether the individual interviewed, specifically, was affected by a given disaster. Thus, like in previous studies (Luechinger and Raschky 2009, von Möllendorff and Hirschfeld 2016), we have to rely on the use of administrative (county-level) boundaries to match SWB and natural disasters. This means that some respondents will be wrongly assigned to the reference group (that is, categorized as not affected even though they are affected by a given disaster) while other individuals will be wrongly assigned to the treatment group (that is, categorized as affected even though they are not). Given the limited geographical scope of natural disasters (compared to the size of the U.S.) and relatively smaller size of the treatment group, the second type of error carries more weight. Thus, we set the boundaries as narrowly as possible, and choose the county (rather than the state), which is the highest level of spatial disaggregation across datasets, to match the individual survey data with extreme weather events, using Geographic Information Systems (GIS). The interview and disaster dates can be precisely matched because BRFSS contains information on the exact day of the interview.

During the period of analysis (2004-2010), there were 11,969 episodes of severe weather and climate caused by forty-two “billion-dollar” disasters in the U.S.³ classified by the NCEI as tropical cyclone, severe storm, flooding, drought, freeze and wildfire. The billion-dollar disaster database reports the time of occurrence and the states affected by the weather and climate events of greatest economic impact, based on the number of deaths and estimated monetary damages (Appendix table 1). We complement this information with the storm events database of NCEI to identify the counties affected by all the events associated with the disasters. Each disaster contains a series of events. For example, a severe storm may comprise tornado, thunderstorm wind, strong

³ Excluding American Samoa, Atlantic N. and S., E pacific, Guam, Gulf of Alaska, Gulf of Mexico, Hawaii, Puerto Rico, Virgin Islands, Lakes Erie, Huron, Michigan, Ontario, St. Clair and Superior and St. Lawrence river.

wind, high wind, hail, flash flood, flood and heavy rain events occurring across multiple locations at different times.⁴ The classification of an event into a given disaster type is based on the “event or episode narrative” provided in the storm event database, NOAA Hurricane Center’s definition of hazards associated with hurricanes, and Smith and Katz’s (2013) specification of disasters types. We reduce the measurement error in combining the billion-dollar disasters and storm event dataset by using the exact date of the disaster as a complementary selection criterion. Appendix table 1 reports the month (or in some cases the season) in which the disaster happened, but for the econometric analysis, we assign an exact disaster date to each affected county, based on the event and episode unique identification numbers. In all the cases, this is the day in which the event ends.

The second panel of Table 1 presents the descriptive statistics of the disaster variables. Nine percent of the respondents live in counties that were affected by one disaster in the two months preceding the interview (variable “Disaster (2 months)”), and the percentage increases to forty-four in the previous year (variable “Disaster (12 months)”). Among disasters, severe storms are the most common type.

3. Identification strategy and econometric model

Although we are using observational data, randomization is done by nature in that extreme weather events act as exogenous shocks randomly assigning individuals into treatment or control groups. The identification strategy is based on two dimensions: the timing and location of both respondents and disasters. To be in the treatment group, (1) the respondent should reside in a county affected by a disaster, and (2) the interview should have taken place during the first k months after the event. In order to explore the temporal decay of the effects of the disasters on SWB, we allow for

⁴ Likewise, a tropical cyclone may contain episodes of flash flood, flood, heavy rain, high wind, hurricane (typhoon), storm surge/tide, rip current, strong wind, tornado, tropical depression and storm; a flood may contain episodes of flash flood, flood, heavy rain, and lakeshore flood; a drought contains episodes of excessive heat, drought, and heat; and a freeze can include winter weather, winter storm, extreme cold/wind chill, heavy snow, blizzard, and frost/freeze.

different values of k : two, four, six, eight, ten, and twelve months (Figure 1, panel A).

[Figure 1 about here]

In panel B of Figure 1, point “T” denotes the treatment group consisting of those respondents who reside in a county affected by a disaster event and who are interviewed within k months of the event. In contrast, the control group includes those respondents who either reside in an unaffected county (D and E) or reside in an affected county but are interviewed before the event (A) or more than k months after the event (B).

To separate the effects of disasters from other confounding factors we utilize a multiple regression framework. We control for individual characteristics, unobserved time-invariant and unobserved time-variant effects by using socio-demographic variables, county fixed effects (FEs) and year dummies, respectively. County FEs control for geographical, climatic, or policy differences across counties that do not vary over the sample period. For example, they help control for whether the respondent lives close to the coast or in a county that participates in the National Flood Insurance Program (NFIP). As noted by Luechinger and Raschky (2009), risk-transfer mechanisms such as flood insurance can alleviate the effects of disasters on SWB. We investigate this in more detail in Section 5.1. We also control for possible correlation and heteroscedasticity among the residuals across counties by clustering the standard errors at the county level. We exclude counties with fewer than 50 respondents.⁵

Our benchmark model takes the following form:

$$SWB_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 disaster_{jkt} + \gamma_j + \delta_t + \varepsilon_{ijt} , \quad (1)$$

⁵ This is consistent with the BRFSS guidelines of not reporting or interpreting FIPS County codes for any county with fewer than 50 respondents. 2010 SMART: BRFSS City and County Data and Documentation, Comparability of data: Retrieved from URL: http://www.cdc.gov/brfss/smart/2010/compare_10.pdf

for $k= 2, 4, 6, 8, 10$ and 12 , where SWB_{ijt} is the measure of well-being (self-reported life satisfaction) of individual i living in country j at time t . X represents a vector of socio-demographic variables (education, marital status, race, employment status, general health, gender, and income). The variable $disaster_{jkt}$ is a treatment dummy variable that takes the value of one if individual i resides in a county affected by a billion-dollar disaster within k months prior to the interview date and zero otherwise. If SWB had changed identically in the treatment and control groups, then there is no effect associated with the disaster, i.e., $\beta_2 = 0$. γ_j and δ_t are county and time FEs, respectively.

Using the estimated coefficients from equation (1), in particular those for income and the disaster dummy, we can obtain the wellbeing effect of a disaster and the willingness to pay to avoid being exposed to a disaster. The marginal rate of substitution (MRS) between income (w) and the disaster variable places a monetary value on a marginal change in the number of disasters ($MRS = \left(\frac{\partial SWB}{\partial disaster} / \frac{\partial SWB}{\partial w} \right)$). We also compute the compensating surplus (CS). In a hypothetical setting, to keep her SWB constant, an individual would be willing to pay the amount CS to avoid being exposed to a disaster, i.e. to avoid a state of the world where the disaster happens, $d^0 = 1$ for one where it does not, $d^1 = 0$, so that $SWB(w, d^0) = SWB(w - CS, d^1)$. Because in equation (1) income enters in a log form, we can express the CS as follows:

$$CS = -\exp \left[\ln(\bar{w}) + \left(\frac{\partial SWB}{\partial disaster} / \frac{\partial SWB}{\partial w} \right) (d^0 - d^1) \right] + \bar{w} \quad (2)$$

As previously noted, the degree of exposure to a disaster can vary widely among individuals within the treatment group. For example, Cohen (2002) distinguishes between primary survivors, who have experienced maximum exposure to the traumatic event; secondary survivors, the grieving close relatives of primary victims; third level survivors who are the rescue and

recovery personnel (e.g. medical and emergency staff, firefighters, police); fourth level victims or other people in the community involved in disaster reports and government personnel; and fifth-level victims who may experience states of distress or disturbance after seeing or hearing media reports. Our data do not allow us to distinguish between exposure categories, thus β_2 measures the *average* impact across the individuals residing in affected counties. Moreover, this parameter is not a laboratory-style estimate of the consequences of a disaster on SWB where all other factors are held constant, because it reflects individuals' actions to protect themselves from disasters.

3.1. Temporal decay of the impact of disasters

The specification in (1) is similar to that in Luechinger and Raschky (2009), but we estimate six versions, using different cumulative time windows for the disaster happening within k months of the interview date ($k=2,4,6,8,10$ and 12), to analyze whether the effect of experiencing a disaster on SWB decays over time. We compare the goodness of fit using the Bayesian Information Criteria across specifications to identify the optimal time window, which is later used for further investigation of the effect of the number and intensity of different type of events on SWB.

We also analyze the temporal decay of the impact of disasters in a more explicit fashion, by utilizing non-overlapping, incremental time windows that illustrate the relative importance of “old” disasters as opposed to disasters that happened closer to the interview date:

$$SWB_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 disaster_{j,[0,2)} + \beta_3 disaster_{j,[2,4)} + \beta_4 disaster_{j,[4,6)} + \beta_5 disaster_{j,[6,8)} + \beta_6 disaster_{j,[8,10)} + \beta_7 disaster_{j,[10,12)} + \gamma_j + \delta_t + \varepsilon_{ijt} , \quad (3)$$

where, $disaster_{j,[k-2),k)}$ is an indicator of being exposed to a disaster within the $(k-2)$ to k months preceding the interview.

3.2. Exogeneity

The estimated treatment effects in equations (1) and (3) are consistent only when the assumption

of exogeneity of natural disasters (i.e., treatment is randomized across individuals) holds; that is, when our proposed quasi-experimental identification strategy combining time and location generates a randomized sample. However, the use of observational data to estimate the treatment effect may be prone to selection bias. A concrete example of selection bias in this context is omitted variable bias that arises due to climate and geographical amenities (e.g. proximity to the coast) that impact both the location decisions of households and the probability of natural disaster occurrences. We minimize this concern by including county FEs in all specifications, which, as stated above, control for time invariant climatic and geographical characteristics.

Another way to address this problem that has become popular in microeconomic evaluation studies is the use of matching methods that aim to equate or “balance” the distribution of covariates in the treated and control groups. In our study, having thirty-seven individual level regressors, clustered within 2,209 counties across the U.S. raises the issue of a high dimensional vector X (“Curse of Dimensionality”) and limits the use of non-parametric matching methods to achieve balance between treated and control groups.⁶ On the other hand, the enormously popular parametric method of propensity score matching described as a solution to the curse of dimensionality “[m]ay also accomplish the opposite of its intended goal and increase the imbalance, inefficiency, model dependence and bias” (King and Nielsen 2016).

Thus, the initial investigation of the data uses nearest neighbor matching with a logistic regression-based propensity score, where we impose a tolerance level of 0.25 on the maximum propensity score distance. First, the distance between the treatment unit and the closest control unit is estimated using propensity score, defined as the probability of receiving treatment conditional on the covariates. To prevent a noticeable reduction in the number of matched observations, we

⁶ For example, we cannot use non-parametric methods such as the nearest neighboring matching for all covariates using Mahalanobis Distance due to the computational complexity of the large dataset.

allow for replacement such that each control unit can be matched to more than one treated unit, and then each observation is assigned a weight that is used to estimate the average treatment effect. Figure 2, evaluating the balance on observables, illustrates no difference in the empirical distribution of propensity scores between the matched treated and control groups and the unmatched treated and control groups. This increases our confidence in the suitability of equations (1) and (3) to provide consistent estimates of the impact of disasters on individual SWB.

[Figure 2 about here]

Moreover, we use a falsification test to assess if the treatment variable captures the negative causal impact of disasters on SWB. To implement this test, we add “fake” disaster variables: $disaster_{j,(-(k+2),-k]}$ which take the value of one if the individual was interviewed within the $(k+2)$ to k months *preceding* the disaster, to equation (3). If the coefficients on the “fake” (or lagged) disaster variables are insignificant, then we cannot find evidence of different pre-disaster trends in SWB between the counties who eventually are affected by a natural disaster and those in the control group.

$$\begin{aligned}
 SWB_{ijt} = & \beta_0 + \beta_1 X_{ijt} + \beta_2 disaster_{j,[-6,-4]} + \beta_3 disaster_{j,[-4,-2]} + \\
 & \beta_4 disaster_{j,[-2,0]} + \beta_5 disaster_{j,[0,2)} + \beta_6 disaster_{j,[2,4)} + \beta_7 disaster_{j,[4,6)} + \\
 & \beta_8 disaster_{j,[6,8)} + \beta_9 disaster_{j,[8,10)} + \beta_{10} disaster_{j,[10,12)} + \gamma_j + \delta_t + \varepsilon_{ijt}
 \end{aligned} \tag{4}$$

3.3. Disaster Type and Magnitude

The perception of disaster risk has been shown to depend on the type of disaster (Alexander 1993, Ho et al. 2008). In our study, the forty-two billion-dollar disasters can be further classified into ten tropical cyclones, seventeen severe storms and tornados, four floods, five droughts, two freezes and four wildfires. Moreover, 1.55% of respondents (26,828 observations) are exposed to different types of events. In order to compare the potentially different effect on well-being of varying

disaster types, we estimate the following equation:

$$SWB_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 tropical\ cyclone_{jkt} + \beta_3 severe\ storm_{jkt} + \beta_4 flood_{jkt} + \beta_5 drought_{jkt} + \beta_6 wildfire_{jkt} + \beta_7 freeze_{jkt} + \gamma_j + \delta_t + \varepsilon_{ijt} \quad (5)$$

where each disaster dummy (tropical cyclone, severe storm, flood, drought, wildfire and freeze) takes the value of one when the individual falls into the treatment group (for that particular disaster type) as previously defined. Table 1 panel B presents their descriptive statistics.

Although the damages for all the disasters in this study surpass one billion dollars, they differ (tropical cyclones are the costliest followed by droughts, floods and severe storms), and one might expect that more costly disasters have a larger impact on SWB. We test this hypothesis reestimating equation (5), where the disaster variables are weighted by their relative damage. That is, they are multiplied by a weight (w_i) constructed by dividing the damage of a specific disaster by the aggregate damage of all forty-two disasters, with damage data from Appendix table 1. (e.g. for Katrina $w_i=152.5/376.1$). If an individual was treated by more than one disaster of a given type during the time considered, the assigned weight corresponds to the most damaging disaster.

4. Results

In this section, we present the results for the different model specifications as defined in the previous section. All the models include the full set of socio-demographic variables, county FEs and year dummies. The coefficients on the socio-demographic controls, reported in Table 2, conform to expectations. Consistent with previous studies (Blanchflower and Oswald 2004, Oswald and Wu 2011), we find a U-shaped relationship between age and life satisfaction, with those 65 or older reporting the highest levels of life satisfaction. More years of schooling are associated with higher levels of life satisfaction in a non-linear fashion. Being separated is, as expected, negatively related to life satisfaction, and being married, widowed or cohabiting are

positively related to life satisfaction, all relative to being single. Some of the most negative correlates of life satisfaction are unemployment (with no evidence of adaptation to this situation from those who are long-term unemployed) and being unable to work. Compared to those in poor health, those reporting other health categories fare much better, and the impact monotonically increases with better health. As expected, the coefficient on household income is positive and statistically significant.⁷ All other races (except for Asian) report a slightly higher level of life satisfaction than whites. Males' life satisfaction is slightly lower than that of females.

[Table 2 about here]

The first row in Table 2 presents the coefficients for β_2 in equation (1) for seven cumulative time windows ($k=2, 4, 6, 8, 10, 12$ and 18 months). Turning to the first column, being treated by a natural disaster of any type in the two months before the interview, reduces the individual life satisfaction by 0.003 on the 4-point scale compared to the control group who are either being interviewed before the disaster, k months after the disaster, or live in another, unaffected region. The negative effect of being affected by a disaster is robust across all models, with $k=6$ months exhibiting the largest negative effect (-0.004) and best fit, as indicated by the BIC.

As the length of the window is expanded from 2 to 12 months, the percentage of respondents treated increases from 9 to 44 percent. The magnitude and significance of the coefficient on the disaster variable, however, does not increase accordingly. In fact, the decreasing magnitude and statistical significance of the disaster coefficients after 8 months suggests that there is indeed a temporal decay of the impact of disasters on SWB. It should be noted that the very consistent results across models with virtually identical estimated coefficients of socio-

⁷ Because the income variable in the BRFSS is measured in 8 intervals, we follow Stewart (1983) for imputation into a continuous variable. When income was included as a collection of dummies with respect to a reference category of \$10,000, the coefficients were also positive, statistically significant, and increasing with income.

demographic variables provides additional support to treating the disaster variables as exogenous.

The CS to avoid exposure to a disaster event for those affected 6 months after the event is \$1,782. This estimated welfare loss is equivalent to 3.54% of average annual household income.⁸ Since we cannot distinguish between those individuals directly and indirectly affected in the sample, the estimated CS reflects the *average* impact of a disaster; it may contain a combination of physical losses as well as psychological negative impacts across different levels of exposure. To put this number in context the federal assistance provided by the Housing Assistance Program to those directly affected by disasters ranges from \$5,000 to \$25,000.

Previous studies on the well-being impact of disasters (Luechinger and Raschky 2009, von Möllendorff and Hirschfeld 2016) choose 18 and 24 months as two additional time windows. We expand our window to 18 months for robustness and, as shown in Table 2, the estimated coefficient of the disaster variable is no longer statistically significant.⁹ This suggests that, for our sample, the impact of disaster on SWB has fully decayed by then, and that failing to choose the appropriate time window may lead to underestimating the disaster welfare loss.

Table 2 reports the results for a disaster dummy variable, but we also analyzed the robustness of the results to using the *count* of disasters in the previous k months in alternative specifications. Because most of the respondents are affected by at most one disaster during the previous 12 months, using the count of disasters instead of a dummy for occurrence of a disaster does not make a large difference in the results (not reported here but available upon request). The results for the disaster dummy variable and the number of disasters variable are similar, especially for shorter time horizons. As the time window broadens, and the number of disasters grows, the

⁸ CS = $-\exp[10.827038 + (-0.0038907)/(0.1079818)(1-0)] + 50364.313 = 1782.383$

⁹ Expanding the window to 18 months, required that we also include the billion-dollar disasters of year 2003.

coefficient on the number of disasters variable is statistically more significant than for the disaster dummy, but we observe a similar pattern of decay in the magnitude of the effects with time.¹⁰

In equation (3) we explicitly test the hypothesis of temporal decay. As results in Table 3 show, having been affected by a disaster in the previous six months (independently of when it happened within the six-month period) has a comparable negative impact on SWB. The hypothesis of equality of effects of having been affected by a disaster within the last 2 months, last 2-4 months and 4-6 months preceding the interview cannot be rejected. The coefficient becomes insignificant ($t=0.65$) for events that occur within 6 to 8 months preceding the interview and continues to drop in magnitude and significance thereafter. This time window is consistent with the results in Table 2 that 6 months is the optimal time window for investigating the impact of disasters. Compared to previous studies, this time frame is shorter than the 18 months considered by Luechinger and Raschky (2009) in their study of flooding in Europe, but longer than in the study by Kimball et al. (2006) in which the dip in happiness in the South-Central region of the U.S. was estimated to last only for two to three weeks after Hurricane Katrina.

[Table 3 about here]

All the regressions include individual characteristics and county FEs. This mitigates concerns about county-level omitted variables bias unless the omitted variables vary over time. For example, because of general economic decline in the U.S. during the late 2000s caused by the great recession, the negative association between disasters and SWB might be spurious if disasters

¹⁰ We also checked for potential non-linearity in the impact of the number of disasters on SWB. We estimated an alternative specification with dummies for 1- 2 disasters, and 3 or more disasters, where zero disaster is the reference group. In results available upon request, we find that the estimated coefficient for experiencing 3 or more disasters is statistically smaller (more negative) than for experiencing 1-2 disasters which illustrates the larger negative impact of experiencing more disasters. We note however, that only 0.66% in our sample experienced more than 3 disasters in the previous 12 months and the percentages are 0.062% and 0.16% for more than 3 disasters within the last 6 and 8 months, respectively.

are more frequent in more depressed areas. To capture the effect of macroeconomic decline during this time span that might be left out of county FE and year dummies, we repeated the regressions including the county level unemployment rate. The results (not reported here) did not change.

As an additional check on the consistence of our estimates, Figure 3 plots the results of the falsification test (equation 4). The coefficients of the “fake”, lagged disaster variables are statistically insignificant. The estimated impact of true disasters, however, is the same as in Table 3. This corroborates that the main conclusions are not confounded by pre-existing differential trends between the SWB of affected and unaffected individuals.

[Figure 3 about here]

Table 4 illustrates the impacts of different disaster types on SWB. Results are reported for the cumulative time windows of 6 and 8 months before the interview (in columns (1) and (2), respectively). Severe storms have a significant negative effect in both specifications. Although the ten tropical cyclones in the sample (especially a series of hurricanes in years 2004, 2005 and 2008) are among the most destructive weather disasters, no significant negative well-being effect is found within 6 and 8 months. Floods also exhibit insignificant coefficients in both columns. Droughts, on the other hand, show a negative, statistically significant (at a 10% level or better) effect on SWB and freeze is only significant in the 6 months specification.¹¹

[Table 4 about here]

When interpreting these results, one should keep in mind that when we disaggregate the total number of disasters by type, we are substantially reducing the size of the treatment group which makes it difficult to identify a statistically significant effect. This is particularly the case for

¹¹ Because a given individual may be treated by a given type of disaster more than once, we also estimate an alternative specification that accounts for that possibility by using the number of disasters instead of dummy variables and find similar results.

the most infrequent and geographically concentrated disasters. While there were seventeen severe storms and tornados, there were fewer tropical cyclones (10), floods (4), wildfires (4), and freezes (2). Despite this, most t -statistics in the table are larger than 1. The sample includes only 5 droughts, but compared to other rapid onset disasters, droughts tend to be persistent. Three of them last for two seasons and two others affect a large population across U.S. states throughout the whole year.

The damage specification models by disaster type are presented in columns (3) and (4) of Table 4. Each disaster is weighted by its relative damage. The results continue to suggest that severe storms have the largest impact on SWB. Interestingly, although floods by themselves were marginally insignificant to explain life satisfaction in columns (1) and (2), they become marginally significant when weighted by their damages in the 8-month specification.

5. Additional exploratory analyses

5.1. Attenuating effects of insurance and governmental assistance programs

Risk transfer mechanisms such as natural-peril insurance and post-hoc disaster relief are designed to attenuate the negative financial implications of natural disasters. Using regional rates of insurance penetration in Germany, von Möllendorff and Hirschfeld (2016) show that insurance density can at least partly offset negative well-being effects of flood events. Similarly, the exploratory analysis of Luechinger and Raschky (2009) suggests that county participation in the NFIP fully compensates the effect of a flood event. Interestingly, our finding of a lack of significance of flood disasters in Table 4 is consistent with their observation.

In the U.S. flood insurance is provided by the NFIP to residents and small businesses in participating communities that adopt minimum floodplain management policies. In addition, NFIP communities can voluntarily participate in the Community Rating System (CRS) to receive

premium discounts in exchange for floodplain management beyond the minimum requirements of NFIP (FEMA, 2017). All our regressions include county FEs, which control for (time-invariant) NFIP and CRS participation of affected counties. Thus, our estimates are an average of the effects of disasters for which the affected population is partially compensated by risk transfer mechanisms and of disaster events for which they are not.

The purchase of flood insurance is ultimately an individual decision.¹² Like in previous papers, however, data limitations prevent us from using individual level insurance data to net out the mitigation effect of insurance products. The best we can do to further investigate this effect and isolate the psychic costs of floods, is to estimate models that explicitly include two county-level flood insurance indicators: (1) NFIP participation, which takes value one when at least one community in the county participated in the NFIP before the flood occurred; and (2) CRS participation, which identifies if the county received discounted insurance premiums through CRS pre-flood.

Although severe storms and tropical cyclones are also associated with flood events in some locations, in this section we focus only on flood disasters because other extreme weather events under the severe storm and tropical cyclone headings (i.e., high wind, hail, etc.) are insured via homeowner insurance. However, the model includes indicator variables for other type of disasters (severe storms and tropical cyclones) to net out the negative impact of other disasters. In the sample, four flood events occurred in years 2006, 2008 and two in 2010. Since the percentage of individuals who are interviewed less than six months after the disaster is 2.5 %, which is relatively low compared to the number of observations in the control group, we choose the eight months window with 3.3% affected individuals. No individual in our sample experiences more than one

¹² Market penetration in the NFIP has been low historically. Estimates of take-up rates reported in Dixon, et al. (2006) range from 20-30 percent in the Midwest, to 50-60 percent in the South and West, and in coastal areas.

flood in this time span. Only 37% of individuals live in a county that provides indemnification against flood events in the form of NFIP at the time of disaster, and among them, only 37% are CRS participating communities.

Table 5 presents the estimated coefficients of the impact of floods on life satisfaction for U.S. counties with and without flood insurance. Compared with the results in Table 4, in this model the flood disaster dummy is negative and becomes statistically significant, which suggests that the impact of flood events on life satisfaction was suppressed by excluding the NFIP dummy variable. The estimated coefficient of the interaction term between the NFIP and flood dummies is positive and significant and of similar size as the flood dummy suggesting that flood insurance fully compensates the effect of flood events for individuals that reside in a NFIP participating county. Conforming to intuition, taking extra measures of floodplain management by participating in CRS programs also has a dampening effect that is statistically similar to that of NFIP participation (column (2)).

[Table 5 about here]

From the coefficients in Table 5 we can also estimate the marginal impact of the flood at means, which is negative and statistically significant (it equals -0.006 and -0.005 for the NFIP and CRS participation models, respectively). From this we conclude that not all the damages of flood events are countervailed by insurance. Psychic cost of disasters, as noted earlier, also reduce the well-being of affected individuals (Luechinger and Raschky 2009). Insurance, however, helps; the costs to the average individual in non-participating communities are higher and statistically different (-0.010 and -0.006).

Governmental relief programs can also attenuate the impact of natural disasters, in some cases acting as substitutes for natural hazard insurance products (Kousky et al. 2018). In the U.S.,

the Disaster Relief and Emergency Assistance Act of 1988 provides disaster relief through the Disaster Relief Fund (DRF) after a federal disaster declaration. We consider two post-disaster governmental relief programs: the Public Assistance (PA) and Individual Assistance (IA) programs which are funded through DRF. PA is a community level assistance program funding “the repair, restoration, reconstruction or replacement of a public facility or infrastructure damaged or destroyed by a disaster” (FEMA 2018), while IA covers a broad range of post-disaster assistance including Mass Care and Emergency Assistance, Voluntary Agencies (VOLAGs), Individual and Households Program (IH), Small Business Administration (SBA), Disaster Unemployment Assistance (DUA), Crisis Counseling Services (CCP), and Disaster Legal Services (DLS).¹³ In the sample, 26%, 56% and 51% of affected counties have received PA, IA, and IH assistance programs respectively. We investigate the effects of IA and IH programs separately to explore the importance of other programs under IA that may or may not be related to housing assistance and other needs assistance.¹⁴ The interaction terms of governmental assistance programs in columns (3) to (5) of Table 5 show that IA and IHP both have a statistically significant attenuating impact on SWB. Although the PA interaction is not statistically significant, the overall marginal effect of disasters for recipients of this program (as well as for recipients of the other two programs) is not statistically different from zero.

5.2. Exploration of attenuating effects of general health insurance

Our data set does contain information on the purchase of health insurance. Although the purchasing decisions for natural peril insurance and health insurance are not comparable due to the different nature of the underlying risks (e.g. distributional differences in the probability of occurrence), and,

¹³ Retrieved from URL: <https://emilms.fema.gov/IS403/lesson3/12010print.htm>

¹⁴ For more details see URL: https://www.fema.gov/media-library-data/1461689021638-cfcfd7f6c263635802fa7a76a19e00ea/FS001_What_is_Individual_Assistance_508.pdf.

in the case of flood insurance, the community participation requirement, we include health care access to try to net out the impact of health care costs following a disaster. Health insurance enrollment can bring peace of mind in the aftermath of catastrophic natural disasters and lessen their negative impact on SWB. A policy related question is to what extent can insurance-covered access to health services act as a coping mechanism to reduce the vulnerabilities of affected populations and work as a countervailing force to neutralize the negative impact of disasters?

In Table 6, we take a first stab at empirically answering this question. We re-estimate model 3 with an additional variable capturing health care access, a dummy that takes value one if the individual reports having access to health care including health insurance, prepaid plans such as Health Maintenance Organizations, or government plans such as Medicare.¹⁵ Results show that the negative impact of a disaster within 2 months is almost fully mitigated for those who have access to health care coverage (captured by interaction between disaster variable and health care access dummy).

[Table 6 about here]

5.3. Impact of disasters on mental health

To check the robustness of our results, we investigate the impact of disasters on mental health. In addition to a life satisfaction question, the BRFSS asks a mental health question: “Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?”

Protecting mental health after a disaster is often a central policy objective. For instance, under the Model State Emergency Health Powers Act (MSEHPA), out-of-state health care

¹⁵ Although some level of coverage for mental health services might be available for respondents through Medicare and Medicaid (e.g., Affordable Care Act and Mental Health Parity Law of 2008), Social Security Disability Insurance (SSDI), and private health insurance plans, the data does not detail the extent to which these plans provide individuals access to mental health services.

providers are allowed to practice as if they were licensed in the state when mental health services are in short-supply immediately after disasters (Rutkow et al. 2011). Other governmental systematic efforts include the Disaster Behavioral Health Information Series (DBHIS) by the Substance Abuse and Mental Health Services Administration (SAMHSA), which provides guidelines to improve the mental health resilience after natural disasters, and the Crisis Counseling Assistance and Training Program (CCP), which assist individuals and communities in recovering from the effects of natural disasters through the provision of community-based outreach and psycho-educational services (FEMA 2018).¹⁶

Considering the positive association between mental health and life satisfaction, we follow the work of Oswald and Wu (2011) and use the same set of regressors for this regression. Since the median of number of days of bad mental health is zero and the distribution is skewed toward the left, we estimate a Logit regression for a binary mental health variable that takes value one if individuals report one or more days of poor mental health and zero otherwise. In our sample, 33% of respondents report experiencing at least one day of bad mental health over the previous month.

Table 7 shows that individuals affected by a disaster are 1.02 times more likely to report 1 or more days of poor mental health than those who are not affected by the disaster. In terms of magnitude, this increase in likelihood of reporting poor mental health is equivalent to 70% of the increase in the likelihood of reporting poor mental health due to unemployment (odds ratio=1.46). Our estimates are community-level average impacts and lack the precision of psychological studies that seek to identify whether an individual is directly affected by disaster-related traumatic events or stressors or she has experienced PTSD. As noted by Cohen (2002), the negative impact of a disaster is different based on the time frames of “Impact Phase” (following the impact), “Short-

¹⁶ Retrieved from URL: <https://www.fema.gov/additional-assistance-disasters#0>

run Phase” (weeks and months after the disaster) and “Long-run Phase”. Our results suggest that the community-level average impact of disasters on mental health, stops being significant after 4 months, somewhere between the short run and long run phases.

[Table 7 about here]

6. Discussion

The increase in weather and climate disasters in recent years has prompted an interest in analyzing their causes, consequences and required mitigation and adaptation measures to minimize their potentially large impacts on welfare. This paper uses SWB data to directly estimate the impact of billion-dollar disasters on individual well-being. As stated in the OECD guideline for measuring SWB, “[t]ime, event and weather-specific effects can be thought of as a source of error in life evaluation, but they are also primary sources of information in the case of short-run affective measures.” On the other hand, extreme weather events have the potential to profoundly impact the quality of life of a sizable proportion of those in affected communities. We argue that the indicator of SWB we use in this paper, life satisfaction, is an appropriate SWB measure for the purposes of estimating the impacts of extreme weather events on human well-being, as it combines a cognitive assessment of overall quality of life with an affective, temporary component.

In this paper, we use a life satisfaction measure of SWB to estimate the effect of forty-two billion-dollar disasters on the welfare of U.S. residents between 2005 and 2010. The statistical investigation of results conforms to the intuition that extreme weather events and disasters negatively impact our well-being. We find that disasters reduce SWB on affected communities (by approximately 0.004 on a four-point scale), that this effect decays over time and that it depends on the type and intensity of disasters.

As the time window between the event and the interview date increases so does the size of the treatment group which, by increasing the precision of the estimates, could lead to finding a significant effect of disasters for longer time horizons. This, however, should not necessarily be interpreted as a long-lasting effect of disasters. Indeed, we show that the negative effects of disasters decays after 6 months. These findings are important as they suggest a policy-relevant time frame to escalate the support systems to aid the community healing process. We also find that during the period of study, severe storms appear to be the disasters that most negatively affect SWB. Droughts also have a negative impact on life satisfaction and exhibit a more persistent effect.

Our results suggest that risk transfer mechanisms can play an important role in mitigating the negative effects of natural disasters. The comparison of uncompensated and compensated impacts (by controlling for county level participation in NFIP and CRS, individual health insurance, and governmental assistance programs) suggests that a significant portion (but not all) of the adverse impact of natural disasters on life satisfaction can be attenuated through private and public risk transfer mechanisms. We then investigate the impact of billion-dollar disasters on the mental health of individuals in affected counties and estimate consistent and complementary results regarding the correlates and the decay of impact.

Compared to post-disaster damage estimates and to traditional methods that measure impacts of disasters on individual welfare (e.g. revealed preference methods), the SWB approach directly focuses on the less tangible negative consequences of weather and climate events, making it a potentially useful additional tool for policy makers to assist communities in assessing their vulnerabilities to the impacts of climate in the areas of human health and planning strategies for adapting to the changing climate.

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Panel A: Temporal assignment to treatment group

Panel B: Temporal and spatial assignment to treatment group

Figure 1: Temporal and spatial assignment to treatment and control groups

Figure 2: Distribution of propensity score for matched and unmatched treated and control groups

Figure 3: Falsification test on impact of disaster on SWB

Table 1: Summary statistics of individual characteristics and disaster variables

	Mean	Std. Dev.	Min	Max
Panel A: Individual characteristics (BRFSS)^(a)				
Life satisfaction (<i>Ordered variable</i>)	3.39	0.63	1	4
Education	14.06	2.11	0	16
Household Income (<i>Continuous variable</i>)	50,352.56	29,496.81	4,676.24	98,709.21
Log (Household Income)	10.60	0.77	8.45	11.50
<i>Marital Status (Categorical variable)</i>				
Married	0.568	0.495	0	1
Divorced	0.145	0.353	0	1
Widowed	0.121	0.326	0	1
Separated	0.022	0.145	0	1
Never married	0.118	0.323	0	1
Cohabiting	0.024	0.153	0	1
<i>Race (Categorical variable)</i>				
White	0.840	0.366	0	1
Black or African American	0.081	0.274	0	1
Asian	0.018	0.133	0	1
Native Hawaiian/ Pacific Islander	0.002	0.046	0	1
American Indian/Alaskan Native	0.013	0.114	0	1
Other races	0.044	0.206	0	1
<i>Age (Categorical variable)</i>				
18 to 24	0.031	0.172	0	1
25 to 34	0.106	0.307	0	1
35 to 44	0.164	0.371	0	1
45 to 54	0.215	0.411	0	1
55 to 64	0.216	0.412	0	1
65 or older	0.266	0.442	0	1
<i>Employment (Categorical variable)</i>				
Employed for wages	0.471	0.500	0	1
Self-employed	0.087	0.281	0	1
Out of work for more than 1 year	0.020	0.141	0	1
Out of work for less than 1 year	0.025	0.156	0	1
Homemaker	0.071	0.257	0	1
Student	0.016	0.125	0	1
Retired	0.248	0.432	0	1
Unable to work	0.061	0.240	0	1
<i>General health (Categorical variable)</i>				
Poor	0.054	0.224	0	1
Fair	0.124	0.330	0	1
Good	0.298	0.458	0	1
Very good	0.333	0.471	0	1

Excellent	0.191	0.393	0	1
<i>Mental health (Binary variable)</i>				
Good (0 days of poor mental health)	0.667	0.471	0	1
Fair/Poor (1 and more days of poor mental health)	0.332	0.471	0	1
<i>Sex (Dummy variable)</i>				
Male	0.389	0.487	0	1
<i>Health Care Access (Dummy variable)</i>				
Health Care Access	0.896	0.305	0	1

Panel B: Disaster variable (NCEI)^(b)

<i>Disaster dummy (=1 if disaster in last k months)</i>				
Disaster (2 months)	0.09	0.28	0.00	1.00
Disaster (4 months)	0.17	0.37	0.00	1.00
Disaster (6 months)	0.25	0.43	0.00	1.00
Disaster (8 months)	0.32	0.47	0.00	1.00
Disaster (10 months)	0.39	0.49	0.00	1.00
Disaster (12 months)	0.44	0.50	0.00	1.00
Disaster (18 months)	0.58	0.50	0.00	1.00
<i>Disaster dummy (=1 if disaster happened k-(k+2) months ago)</i>				
Disaster (0-2 months)	0.09	0.28	0.00	1.00
Disaster (2-4 months)	0.09	0.29	0.00	1.00
Disaster (4-6 months)	0.10	0.30	0.00	1.00
Disaster (6-8 months)	0.10	0.30	0.00	1.00
Disaster (8-10 months)	0.10	0.30	0.00	1.00
Disaster (10-12 months)	0.10	0.30	0.00	1.00
<i>Disasters by type in cumulative 6- and 8-months time windows</i>				
Tropical cyclone (6 months)	0.03	0.18	0.00	1.00
Tropical cyclone (8 months)	0.05	0.21	0.00	1.00
Severe storm (6 months)	0.11	0.31	0.00	1.00
Severe storm (8 months)	0.14	0.35	0.00	1.00
Flood (6 months)	0.02	0.15	0.00	1.00
Flood (8 months)	0.03	0.18	0.00	1.00
Drought (6 months)	0.08	0.27	0.00	1.00
Drought (8 months)	0.10	0.30	0.00	1.00
Wildfire (6 months)	0.02	0.15	0.00	1.00
Wildfire (8 months)	0.03	0.18	0.00	1.00
Freeze (6 months)	0.02	0.13	0.00	1.00
Freeze (8 months)	0.02	0.15	0.00	1.00

Notes: (a) Individual-level data from the annual Behavioral Risk Factor Surveillance System (BRFSS) of the Centers of Disease Control and Prevention (CDC) covering period 2005-2010. (b) Disaster data from the National Centers of Environmental Information (NCEI) for the period 2004-2010 are matched to individual level data. See Appendix table 1 for more information on disaster events and damage estimates.

Table 2: Effect of disaster on individual SWB across cumulative time windows

<i>k</i>	(1) 2 months	(2) 4 months	(3) 6 months	(4) 8 months	(5) 10 months	(6) 12 months	(7) 18 months
Disaster (dummy)	-0.003* (0.002)	-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.002** (0.001)	-0.002* (0.001)	-0.001 (0.001)
<i>Age (ref: 18-24)</i>							
25 to 34	-0.063*** (0.003)	-0.063*** (0.003)	-0.063*** (0.003)	-0.063*** (0.003)	-0.063*** (0.003)	-0.063*** (0.003)	-0.063*** (0.003)
35 to 44	-0.085*** (0.003)	-0.085*** (0.003)	-0.085*** (0.003)	-0.085*** (0.003)	-0.085*** (0.003)	-0.085*** (0.003)	-0.085*** (0.003)
45 to 54	-0.077*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)	-0.077*** (0.003)
55 to 64	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)
65 or older	0.077*** (0.003)	0.077*** (0.003)	0.077*** (0.003)	0.077*** (0.003)	0.077*** (0.003)	0.077*** (0.003)	0.077*** (0.003)
Education	-0.039*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)
Education^2	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
<i>Log (Income)</i>	0.108*** (0.001)	0.108*** (0.001)	0.108*** (0.001)	0.108*** (0.001)	0.108*** (0.001)	0.108*** (0.001)	0.108*** (0.001)
<i>Marital Status (ref: Never married)</i>							
Married	0.173*** (0.002)	0.173*** (0.002)	0.173*** (0.002)	0.173*** (0.002)	0.173*** (0.002)	0.173*** (0.002)	0.173*** (0.002)
Divorced	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
Widowed	0.051*** (0.003)	0.051*** (0.003)	0.051*** (0.003)	0.051*** (0.003)	0.051*** (0.003)	0.051*** (0.003)	0.051*** (0.003)
Separated	-0.068*** (0.005)	-0.068*** (0.005)	-0.068*** (0.005)	-0.068*** (0.005)	-0.068*** (0.005)	-0.068*** (0.005)	-0.068*** (0.005)
Cohabit	0.071*** (0.004)	0.071*** (0.004)	0.071*** (0.004)	0.071*** (0.004)	0.071*** (0.004)	0.071*** (0.004)	0.071*** (0.004)
<i>Race (ref: White)</i>							
African American	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)
Asian	-0.027*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)
Native Hawaiian/Pacific Islander	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)
American Indian/Native	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)

Alaskan							
Other	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)
<i>Employment (ref: employed for wages)</i>							
Self-employed	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)
Unemployed	-0.187*** (0.004)	-0.187*** (0.004)	-0.187*** (0.004)	-0.187*** (0.004)	-0.187*** (0.004)	-0.187*** (0.004)	-0.187*** (0.004)
>1 year							
Unemployed-	-0.171*** (0.003)	-0.171*** (0.003)	-0.171*** (0.003)	-0.171*** (0.003)	-0.171*** (0.003)	-0.171*** (0.003)	-0.171*** (0.003)
less than 1 year							
Homemaker	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)
Student	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)
Retired	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)	0.059*** (0.002)
Unable to work	-0.137*** (0.003)	-0.137*** (0.003)	-0.137*** (0.003)	-0.137*** (0.003)	-0.137*** (0.003)	-0.137*** (0.003)	-0.137*** (0.003)
<i>General Health (ref: Poor)</i>							
Fair	0.205*** (0.003)	0.205*** (0.003)	0.205*** (0.003)	0.205*** (0.003)	0.205*** (0.003)	0.205*** (0.003)	0.205*** (0.003)
Good	0.341*** (0.003)	0.341*** (0.003)	0.341*** (0.003)	0.341*** (0.003)	0.341*** (0.003)	0.341*** (0.003)	0.341*** (0.003)
Very good	0.509*** (0.003)	0.509*** (0.003)	0.509*** (0.003)	0.509*** (0.003)	0.509*** (0.003)	0.509*** (0.003)	0.509*** (0.003)
Excellent	0.648*** (0.003)	0.648*** (0.003)	0.648*** (0.003)	0.648*** (0.003)	0.648*** (0.003)	0.648*** (0.003)	0.648*** (0.003)
Male	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.982*** (0.022)	1.983*** (0.022)	1.983*** (0.022)	1.983*** (0.022)	1.983*** (0.022)	1.983*** (0.022)	1.983*** (0.022)
Observations	1,730,820	1,730,820	1,730,820	1,730,820	1,730,820	1,730,820	1,730,820
Adjusted R-squared	0.182	0.182	0.182	0.182	0.182	0.182	0.182
BIC	2955646	2955640	2955637	2955640	2955644	2955646	2955648
MRS*(-1) (\$)	1352.065 (780.930)	1657.868 (609.351)	1814.658 (536.062)	1543.203 (519.255)	1128.509 (505.12)	865.474 (508.283)	626.372 (568.338)
CS (WTP) (\$)	1334.077 (760.243)	1630.879 (589.620)	1782.356 (517.091)	1519.8 (503.586)	1115.96 (493.928)	858.080 (499.623)	622.493 (561.313)
% Average annual household income	2.65%	3.24%	3.54%	3.02%	2.21%	1.70%	1.23%

Notes: Dependent variable is life satisfaction. Standard errors in parentheses are clustered at the county level. MRS*(-1) = willingness to pay to avoid the disaster in the margin.. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of disaster on individual SWB for incremental time windows

	(1)
Disaster [0 , 2)	-0.003** (0.002)
Disaster [2 , 4)	-0.004*** (0.002)
Disaster [4 , 6)	-0.003** (0.002)
Disaster [6 , 8)	-0.001 (0.002)
Disaster [8 , 10)	-0.001 (0.001)
Disaster [10 , 12)	0.001 (0.002)
Socio-demographic variables	Yes
County FE	Yes
Year dummies	Yes
Constant	1.983*** (0.022)
Observations	1,730,820
BIC	2955707

Notes: Dependent variable is life satisfaction. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of different type of disaster on individual life satisfaction

	(1)	(2)	(3)	(4)
<i>k</i>	6 months	8 months	6 months	8 months
	Weighted by relative damage			
Tropical cyclone	-0.001 (0.003)	0.000 (0.002)	-0.008 (0.014)	-0.007 (0.012)
Severe storm	-0.005*** (0.002)	-0.005*** (0.001)	-0.684*** (0.223)	-0.694*** (0.197)
Flood	-0.003 (0.003)	-0.004 (0.003)	-0.290 (0.187)	-0.331** (0.166)
Drought	-0.004** (0.002)	-0.003* (0.00170)	-0.169 (0.106)	-0.112 (0.098)
Wildfire	0.003 (0.003)	0.005* (0.003)	0.444 (0.559)	1.035** (0.523)
Freeze	-0.008* (0.004)	-0.005 (0.004)	-1.135 (0.741)	-0.728 (0.617)
Socio-demographic variables	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	2.420*** (0.01683)	2.420*** (0.01684)	1.982*** (0.022)	1.982*** (0.022)
Observations	1,730,820	1,730,820	1,730,820	1,730,820
BIC	2955701	2955697	2955700	2955696

Notes: Dependent variable is life satisfaction. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Private and public risk transfer mechanism and flood disaster impact

	(1)	(2)	(3)	(4)	(5)
	NFIP participation	CRS participation	PA program	IA program	IH program
Flood	-0.010** (0.004)	-0.006** (0.003)	-0.007* (0.004)	-0.006** (0.003)	-0.008** (0.004)
NFIP participation	-0.001 (0.003)				
Flood* NFIP participation	0.010** (0.005)				
CRS participation		-0.002 (0.004)			
Flood * CRS participation		0.012** (0.006)			
Flood* PA			0.007 (0.005)		
Flood * IA				0.010* (0.005)	
Flood * IHP					0.008* (0.005)
Controls for other disasters	Yes	Yes	Yes	Yes	Yes
Socio-demographic variables	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	1.982*** (0.022)	1.982*** (0.022)	1.982*** (0.022)	1.982*** (0.022)	1.982*** (0.022)
Observations	1,730,820	1,730,820	1,730,820	1,730,820	1,730,820
BIC	2955672	2955672	2955675	2955675	2955675

Notes: Dependent variable is life satisfaction. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Health care access and disaster impact

	(1)	(2)
Health Care Access		0.068*** (0.002)
Disaster [0 , 2)	-0.003* (0.002)	-0.016*** (0.006)
Disaster [2 , 4)	-0.004*** (0.002)	-0.009* (0.005)
Disaster [4 , 6)	-0.003** (0.001)	-0.001 (0.005)
Disaster [6 , 8)	-0.001 (0.002)	-0.005 (0.005)
Disaster [8 , 10)	-0.001 (0.002)	-0.002 (0.005)
Disaster [10 , 12)	0.001 (0.001)	0.001 (0.005)
Disaster [0 , 2) * Health Care Access		0.014** (0.006)
Disaster [2 , 4) * Health Care Access		0.005 (0.006)
Disaster [4 , 6) *Health Care Access		-0.003 (0.005)
Disaster [6 , 8) * Health Care Access		0.004 (0.005)
Disaster [8 , 10) * Health Care Access		0.002 (0.005)
Disaster [10 , 12) * Health Care Access		-0.000 (0.005)
Socio-demographic variables	Yes	Yes
County FE	Yes	Yes
Year dummies	Yes	Yes
Constant	1.983*** (0.022)	2.012*** (0.022)
Observations	1,730,820	1,730,819
BIC	2955707	2953778

Notes: Dependent variable is life satisfaction. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Disaster impacts on self-reported Mental Health

	Log of odd ratio
Disaster [0 , 2)	0.018** (0.006)
Disaster [2 , 4)	0.020** (0.006)
Disaster [4 , 6)	0.002 (0.006)
Disaster [6 , 8)	0.001 (0.006)
Disaster [8 , 10)	0.004 (0.006)
Disaster [10 , 12)	-0.001 (0.006)
Socio-demographic variables	Yes
County FE	Yes
Year dummies	Yes
Constant	2.157*** (0.180)
Observations	1,711,204

Notes: Dependent variable is mental health. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix table 1: Billion-dollar weather and climate disasters in the U.S. from 2004 to 2010

#	Month and year of disasters	Name	States	Number of affected counties ^(a)	Damage in Billions ^{(b)(c)}	Deaths ^(b)
1	October 2010	Arizona Severe Weather	AZ	9	\$4.1	0
2	July 2010	Midwest/Northeast Severe Storms and Flooding	IA, IL, MD, NY, PA, and WI	335	\$1.0	0
3	May 2010	Oklahoma, Kansas, and Texas Tornadoes and Severe Weather	OK, KS, and TX	319	\$3.6	3
4	May 2010	East/South Flooding and Severe Weather	TN, AR, AL, KY, MS, and GA	395	\$2.5	32
5	March 2010	Northeast Flooding	RI, CT, MA, NJ, NY, and PA	68	\$1.6	11
6	2009	Southwest/Great Plains Drought	TX, OK, KS, CA, NM, and AZ	284	\$3.9	0
7	Summer-Fall 2009	Western Wildfires	CA, AZ, NM, TX, OK, and UT	88	\$1.1	10
8	July 2009	Colorado Severe Weather	CO	37	\$1.1	0
9	June 2009	Midwest, South and East Severe Weather	TX, OK, MO, NE, KS, AR, AL, MS, TN, NC, SC, KY, PA	985	\$1.4	0
10	April 2009	South/Southeast Severe Weather and Tornadoes	AL, AR, GA, KY, MO, SC, and TN	454	\$1.6	6
11	March 2009	Midwest/Southeast Tornadoes	NE, KS, OK, IA, TX, LA, MS, AL, GA, TN, and KY	564	\$1.8	0
12	February 2009	Southeast/Ohio Valley Severe Weather	TN, KY, OK, OH, VA, WV, and PA	499	\$1.9	10
13	2008	U.S. Drought	U.S	794	\$7.8	0
14	Fall 2008	U.S. wildfire	AK, AZ, CA, NM, ID, UT, MT, NV, OR, WA, CO, TX, OK, and NC	92	\$1.3	16
15	September 2008	Hurricane Ike	TX, LA, AR, TN, IL, IN, KY, MO, OH, MI and PA.	744	\$33.3	112
16	September 2008	Hurricane Gustav	AL, AR, LA, and MS	184	\$6.7	53
17	July 2008	Hurricane Dolly	TX and NM	40	\$1.4	3
18	Summer 2008	Midwest Flooding	IA, IL, IN, MO, MN, NE, WI and IA	375	\$11.1	24
19	June 2008	Midwest/Mid Atlantic Severe Weather	IA, IL, IN, KS, NE, MI, MN, MO, OK, WI, MD, VA, and WV	1,009	\$1.6	18

20	May 2008	Midwest Tornadoes Severe Weather	IA, IL, IN, KS, NE, MI, MN, MO, OK, WI, MD, VA, and WV	602	\$3.3	13
21	April 2008	Southern Severe Weather	AR, OK, and TX	299	\$1.1	2
22	March 2008	Southeast Tornadoes	GA and SC	142	\$1.2	5
23	February 2008	Southeast Tornadoes and Severe Weather	AL, AR, IN, KY, MS, OH, TN, and TX	491	\$1.3	57
24	Summer-Fall 2007	Western/Eastern Drought/Heatwave	ND, SD, NE, KS, OK, TX, MN, WI, IA, MO, AR, LA, MS, AL, GA, NC, SC, FL, TN, VA, WV, KY, IN, IL, OH, MI, PA, NY	1,176	\$4.0	15
25	Summer 2007	Western Wildfires	AK, AZ, CA, ID, UT, MT, NV, OR, and WA	142	\$3.1	12
26	April 2007	East/South Severe Weather and Flooding	CT, DE, GA, LA, ME, MD, MA, MS, NH, NJ, NY, NC, PA, RI, SC, TX, VT, and VA	701	\$2.9	9
27	April 2007	Spring Freeze	AL, AR, GA, IL, IN, IA, KS, KY, MS, MO, NE, NC, OH, OK, SC, TN, VA, and WV	1,049	\$2.3	0
28	January 2007	California Freeze	CA	50	\$1.6	1
29	2006	Numerous Wildfires	AK, AZ, CA, CO, FL, ID, MT, NM, NV, OK, OR, TX, WA, and WY	319	\$1.8	28
30	Spring-Summer 2006	Midwest/Plains/Southeast Drought	ND, SD, NE, KS, OK, TX, MN, IA, MO, AR, LA, MS, AL, GA, FL, MT, WY, CO, and NM	839	\$7.1	0
31	June 2006	Northeast Flooding	NY, PA, DE, MD, NJ, and VA	168	\$1.8	20
32	April 2006	Midwest and Midwest/Southeast Tornadoes	OK, KS, MO, NE, KY, OH, TN, IN, MS, GA, AL, AR, KY, TX, IA, IL, and WI	1,330	\$4.7	27
33	March 2006	Severe Storms and Tornadoes	AL, AR, KY, MS, TN, TX, IN, KS, MO, and OK.	755	\$1.5	10
34	September 2005	Hurricane Rita	FL, AL, MS, LA, AR, and TX	671	\$22.6	119
35	Spring-Summer 2005	Midwest drought	AR, IL, IN, MO, OH, and WI	269	\$1.8	0
36	August 2005	Hurricane Katrina	AL, MS, FL, TN, KY, IN, OH, and GA	516	\$152.5	1,833
37	July 2005	Hurricane Dennis	FL, AL GA, MS, and TN.	344	\$3.1	15
38	September 2004	Hurricane Jeanne	GA, SC, NC, VA, MD, DE, NJ, PA, and NY	509	\$9.5	28
39	September 2004	Hurricane Ivan	GA, MS, LA, SC, NC, VA, WV, MD, TN, KY, OH, DE, NJ, PA, and NY	780	\$25.8	57

40	September 2004	Hurricane Frances	GA, SC, NC, and NY	321	\$12.3	48
41	August 2004	Hurricane Charley	FL SC and NC.	147	\$20.8	35
42	May 2004	Severe Storms, Hail, Tornadoes	ND, SD, NE, KS, MO, IA, MN, WI, IL, IN, MI, OH, Ok, TX, AR, LA, MS, AL, TN, KY, VA, NC, SC, GA, FL, ME, VT, NH, MA, NY, RI, CT, NJ, DE, MD, WV, PA, NY	2,223	\$1.2	4

Notes: (a) The number of affected counties in each state are identified based on the Storm Events database as entered by NOAA's National Weather Service (NWS). (b) The reported monetary damages in Appendix table 1 are based on direct insured and uninsured losses which include physical damage to residential, commercial and government/municipal buildings, material assets within a building, time element losses (i.e., time-cost for businesses and hotel-costs for loss of living quarters), vehicles, public and private infrastructure, and agricultural assets (e.g., buildings, machinery, livestock), and exclude losses to natural capital/assets, healthcare related losses, or values associated with loss of life. Key data sources of quantified insured disaster loss data are the Insurance Services Office, Property Claim Services, Federal Emergency Management Agency, National Flood Insurance Program, Presidential Disaster Declaration assistance, the U.S Department of Agriculture, National Agricultural Statistics Service, and Risk Management Agency (Smith and Katz, 2013). (c) Damage values represent the 2015 Consumer Price Index (CPI) cost adjusted values in billion dollars. (d) Retrieved from URL: <https://www.ncdc.noaa.gov/billions/events>.