Well-being Effects of Extreme Weather Events in the US

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Abstract

This paper estimates the effect of extreme weather and climate events on the subjective well-being of US residents. We match forty two billion-dollar disaster events with individual survey data between 2005 and 2010. We find that being affected by a disaster has a negative and robust impact on life satisfaction that disappears 6 to 8 months after the event. In our sample severe storms are the main culprit in the reduction of life satisfaction; droughts also have a negative impact on life satisfaction and exhibit a more persistent effect.

Key words: Subjective well-being, extreme weather, disasters, climate change.

JEL: Q54, I31

1. Introduction

Natural disasters caused by earthquakes, tsunamis, volcanic eruptions, hurricanes, floods and droughts (among others) occur frequently across the world and can have profound environmental, economic, political, and social consequences. Between 1994 and 2013, the global disaster database EM-DAT, recorded 6,783 natural disasters worldwide, which claimed 1.35 million lives (or almost 68,000 lives on average each year) and affected 218 million people on average each year (CRED & UNISDR, 2015).

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. Since 2000, EM-DAT recorded 341 climate-related disasters per annum on average, an increase of 44% from the average in 1994-2000, and more than twice that in 1980-1989 (CRED & UNISDR, 2015). Weather and climate disaster time series from 1980-2011 in the US also suggest increasing trends in both the annual frequency and annual aggregate loss of "billion-dollar" disasters (Smith and Katz, 2013), with climate change expected to further contribute to changes in the frequency, intensity, duration, and timing of extreme weather events (IPCC, 2012).

Disasters can have an impact on human well-being through the financial losses associated with property damages and fiscal consequences of reconstruction. Moreover, they can cause stress and other psychological costs (uncertainty, grief for the bereaved, individual and collective traumas) (Carrol et al., 2009; Luechinger and Raschky, 2009). However, estimates of the damages of natural disasters typically ignore these intangible costs.[1]

Economists have typically 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 the risks of hazards. 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 in Bin and Polasky (2004), Bin and Landry (2013), and Atreya et al. (2014); hurricanes and tropical cyclones in Hallstrom and Smith (2005), and Simmons et al. (2002); wildfire in Loomis (2004) and Donovan et al. (2007).

Recent years have seen economists increasingly use data on subjective well-being (SWB) to study the impact of economic and social factors (such as income and unemployment),

[1] For example, the loss estimates in the billion-dollar weather and climate disasters published by the US 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.

institutions and public goods on human welfare (for reviews see e.g., Frey and Stutzer, 2002; Dolan et al., 2008; van Praag and Ferrer-i-Carbonell, 2008; MacKerron, 2012). While large portions of this literature are concerned with economic variables in the narrow sense, public goods or bads – in particular environmental quality – are receiving increasing attention (Welsch and Ferreira 2013). Factors that have been linked to SWB include aircraft noise (Van Praag and Baarsma, 2005), air pollution (Welsch, 2002, 2006; Luechinger 2009; Levinson 2012; Ferreira et al. 2013), and the prevailing climate (Frijters and Van Praag, 1998; Rehdanz and Maddison, 2005; Murray et al. 2013).

The evaluation of the impacts of natural disasters on human well-being is a particularly suitable application of SWB data. Public health scientists have started studying how severe weather events brought about by climate change will affect mental health. They 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).

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. (2013) 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 equivalent to 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 US residents from 2005 to 2010. The focus on the US is also new. The US is a particularly appropriate setting for this research. Because of its geography, climate and size, the US consistently is among the top disaster prone nations. For example, in 2015 the US was the second country most affected by natural disasters, with 22 reported disasters, behind China with 26 (UNISDR 2015). During 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 US National Centers for Environmental Information (NCEI) (Table 2). In addition, although the US is large, by analyzing SWB data of only country, we avoid problems of intercultural comparability of responses to SWB questions and cross cultural differences in risk perceptions of disasters (Gierlach et al. 2010).

We merge individual survey data from the Behavioral Risk Factor Surveillance System (BRFSS), with the storm events and the billion-dollar disaster events databases of the NCEI. We use Geographic Information System (GIS) to match the individual data with the extreme weather events at the county-level which is the smallest spatial resolution across datasets. When analyzing the heterogeneity of impacts of different types of disasters on SWB, we control for their damages (monetary as well as in terms of the number of people affected –killed or injured), and hypothesize that more severe disasters will have a larger impact. Because the BRFSS records the exact date of the interview, we can match interview and disaster dates to explore the temporal decay of the impacts of natural disasters on SWB.

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 pemature morbidity and mortality. Data are collected for all 50 states. Between 2005 to 2010 the questionnaire contained a standard 4-point scale life-satisfaction question: “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 this SWB question and other individual sociodemographic controls included in the regressions.

[Table 1 about here]

In addition to the state, the BRFSS records the county of residence of the respondents. We use GIS to match the individual data with the extreme weather events at this spatial level. 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 data. 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 US) and relatively smaller size of the treatment group, the second type of error carries more weight. Thus, we set the boundaries as narrow as possible, and choose the county (rather than the state), which is the smallest spatial resolution across datasets. Moreover, because BRFFS contains information on the exact day of the interview, we can precisely match the interview date with the disaster date.

During the period of analysis (2004-2010), there were 91,982 episodes of severe weather and climate events in the US.[2] 11,969 of these episodes were caused by forty-two "billion-dollar" disasters classified as tropical cyclone, severe storm, flooding, drought, freeze and wildfire by the NCEI (Table 2). The billion-dollar disaster classification includes weather and climate events that have had the greatest economic impact, based on the number of deaths and estimated monetary damages.[3]

[Table 2 about here]

The NCEI billion-dollar disaster database reports information on the time of occurrence and states affected by the forty-two disasters listed in table 2. 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 in table 2 contains a series of events. For example, a severe storm may contain tornado, thunderstorm wind, strong wind, high wind, hail, flash flood, flood and heavy rain events occurring across multiple locations at different times. Table 2 reports

[2] Excluding American Samoa, Atlantic north and south, E pacific, Guam, Gulf of Alaska, Gulf of Mexico, Hawaii, Hawaii waters, Puerto Rico, Virgin Islands, Lake Erie, Lake Huron, Lake Michigan, Lake Ontario, Lake St. Clair, Lake Superior and St. Lawrence river.

[3] The reported monetary damages in table 2 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 (ISO) Property Claim Services (PCS), Federal Emergency Management Agency (FEMA) National Flood Insurance Program (NFIP) and Presidential Disaster Declaration (PDD) assistance, and the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) & Risk Management Agency (RMA). (Smith and Katz, 2013).

the month (or in some cases the season) in which the disaster happened, but for the econometric analysis, we are able to assign an exact disaster date to each affected county, based on the "event or episode narrative" provided in the database, and the event and episode unique identification numbers. In all the cases we choose the day in which the event started.

Table 3 presents the descriptive statistics of the disaster variables employed in the econometric analysis. Starting with the total number of disasters, we see that as the time window from the date of the interview expands, the number of disasters experienced in the average county increases. In the 12 months preceding the interview, the average respondent resided in a county affected by at least one disaster (with a maximum of 7). Fourteen 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 seventy in the previous year (variable "Disaster (12 months)"). Table 3 also reports the frequency of disasters and their damages by type.[4] Tropical cyclones are the costliest followed by severe storms; the average county/zone hit by a tropical cyclone suffers property damages in the order of 6.87 million dollars (the maximum is above 2 billion dollars).

[Table 3 about here]

Due to the difficulty in distinguishing between the direct and indirect[5] causes of weather-related fatalities and injuries, we use the total number of deaths and injuries associated with the

[4] The estimated damage cost in the Storm Event database are from different sources including insurance companies, the estimation by Storm Data Preparer, Verisk Analytics' Property Claim Services (PCS) department for insured loss, National Flood Insurance Program (NFIP), U.S. Department of Agriculture (USDA), the county/parish agricultural extension agent, the state department of agriculture, crop insurance agencies, or any other reliable authority. (National Weather Service Instruction-Storm Data Preparation Report, March, 2016)

[5] Direct deaths or injuries are those directly caused by the environmental force of the hydro-meteorological event (e.g. wind or flood), such as drowning or being impacted by airborne/falling/moving debris, i.e., missiles generated by wind, water, ice, lightning, tornado, or by the direct consequences of these forces (e.g. structural collapse). Indirect deaths or injuries are those indirectly caused by a hydro-meteorological event in its vicinity or after it has ended, such as those occurring in a situation in which the disaster led to unsafe conditions (e.g., hazardous roads) or caused a loss or disruption of usual services that contributed to the death (e.g., loss of electrical services)

disaster of interest at the county level. Finally, we note that although we are using observational data, randomization has been done by nature such that extreme weather events and disasters act as exogenous treatments on individuals and randomly assign them into treatment and control groups.

3. Identification strategy and econometric model

The identification strategy in this study is based on two dimensions: timing and location of both respondents and disasters. To be in the treatment group, (1) the respondent should be living in a county that was affected by a disaster, and (2) the interview should have taken place anytime 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 different values of k: two, four, six, eight, ten, and twelve months (Figure 1). We have to keep in mind that as we expand the time frame, we are likely to observe more individuals that experienced an event (the percentage of respondents affected by a disaster increases from 14 for k=2 to 70 for k=12 in Table 3). This increase in the size of the treatment group could increase the significance of our results. On the other hand, if there is a temporal decay of the impacts of an event, we would expect a smaller effect as the time frame increases. Figure 1 shows the identification strategy in this quasi-experimental study in which the disaster randomly assigns individuals to treatment and control groups:

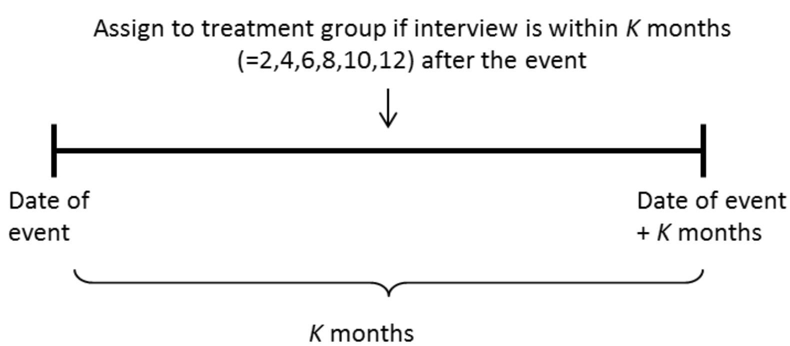

Figure 1: Temporal assignment to treatment and control group

To separate the effects of disasters from other confounding factors we utilize a multivariate regression framework. We control for individual characteristics, unobserved time-invariant and unobserved time-variant effects by using socio-demographic variables, county fixed effects and year dummies, respectively. County fixed effects 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 in a county that participates in the National Flood Insurance Program (NFIP). As noted by Luchinger and Raschky (2009), risk-transfer mechanisms such as flood insurance can alleviate the effects of disasters on SWB. We also control for possible correlation and heteroscedasticity among the residuals across the counties by clustering the standard errors at the county level. We exclude counties with fewer than 50 respondents.

Our benchmark model takes the following form:

$$SWB_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 disaster_{jk} + \gamma_j + \delta_t + \varepsilon_{ijt} \tag{1}$$

for *k*= 2, 4, 6, 8, 10 and 12, where SWB_{ijt} is the measure of well-being 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 $disaster_{jk}$ is a treatment dummy variable that takes the value of one if individual i lives 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 (i.e. $\beta_2 = 0$), then there is no effect associated with the disaster. γ_j and δ_t are county and time fixed effects.

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 (for *k*=2,4,6,8,10 and 12) to analyze the decay effect of the disaster on SWB using different cumulative time windows (less than k months before the interview date). We compare the goodness of fit (using Bayesian Information Criteria) across specifications to identify the optimal time window, which is later used for further investigation of the effect of frequency and intensity of different type of events on SWB.

We also analyze the temporal decay of the impact of disasters by utilizing non-overlapping, incremental time widows that illustrate the relative importance of "old" disasters as opposed to disasters that happened closer to the interview date.

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

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

3.2. Disaster frequency and type

In our sample, 24 percent of individuals live in counties that experienced more than one disaster in the previous year. In order to investigate the impact of the frequency with which individuals are affected by disasters, we estimate the following specification:

$$SWB_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 number\ of\ disasters_{jk} + \gamma_j + \delta_t + \varepsilon_{ijt} \tag{3}$$

We also analyze the different effect on well-being of various disaster types. The perception of disaster risk has been shown to depend on the type of disaster (Alexander, 1993; Ho et al. 2008). In our study, in addition to a sizeable percentage of the sample being exposed to more than one disaster in the previous 12 months, 17.5% of respondents are exposed to different types of events. Therefore, we estimate equation (4):

$$SWB_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2\, tropical\ cyclone_{jk} + \beta_3\, severe\ storm_{jk} + \beta_4\, flood_{jk} + \beta_5\, drought_{jk} + \beta_6 wildfire_{jk} + \beta_7\, freeze_{\ jk} + \gamma_j + \delta_t + \varepsilon_{ijt} \tag{4}$$

where each disaster dummy (tropical cyclone, severe storm, flood, drought, wildfire and freeze) takes the value one when the individual falls into treatment group as previously defined. However, because a given individual may be treated by a given type of disaster more than once, we consider an alternative specification that accounts for that possibility.

$$SWB_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2\, Number\ of\ tropical\ cyclone_{jk} + \beta_3 Number\ of\ severe\ storm_{\ jk} + \beta_4 Number\ of\ flood_{jk} + \beta_5\, Number\ of\ drought_{jk} + \beta_6 Number\ of\ wildfire_{jk} + \beta_7\, Number\ of\ freeze_{jk}\ + \gamma_j + \delta_t + \varepsilon_{ijt} \tag{5}$$

3.3. Disaster magnitude

All the disasters considered in the econometric analysis are billion dollar disasters. Their damages, however, are not evenly distributed across space. For example, severe storms and tornadoes in 2006 affected 755 counties, with monetary damages ranging from \$0 in Russell County, Kentucky to half billion dollars in Green County, Missouri. That is, the intensity of the treatment differs across affected countries. In the following specification we exploit this variation in damages to get a more nuanced picture of the effect of damage intensity by disaster type. As mentioned before, the NCEI Storm events database reports four different categories of damages: property damage, crop damage, deaths and injuries. We estimate equation (6) four times, one for each type of damage. In equation (6), the disaster variables are no longer a count, they are weighted by the damages caused by every disaster (of a given type).

$$SWB_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 tropical\ cyclone_{jk} \times damage_{\ jk} \qquad (6)$$
$$+ \beta_3\ severe\ storm_{jk} \times damage_{jk} + \beta_4\ flood_{jk} \times damage_{jk}$$
$$+ \beta_5\ drought_{jk} \times damage_{jk} + \beta_6 wildfire_{jk} \times damage_{jk}$$
$$+ \beta_7\ freeze_{jk} \times damage_{jk}\ + \gamma_j + \delta_t + \varepsilon_{ijt}$$

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 fixed effects and year dummies. The coefficients on the socio-demographic controls, reported in Table 4, 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. One of the most negative correlates of life satisfaction is 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. Income enters in the regressions in seven levels (each relative to an income of less than \$10,000). As expected, all the coefficients are positive, statistically significant, and increasing in income. 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 4 about here]

The first row in Table 4 presents the coefficients for β_2 in equation (1) for six cumulative time windows (k=2,4,6,8,10,12). Turning to the first column, being treated by a natural disaster of any type in the last two months before the interview, reduces the individual life satisfaction by 0.0033 on the 4-point scale compared to the control group who are either being interviewed before the disaster or live in another, unaffected region.[6] The negative effect of being affected by a disaster is robust across all models, with k=8 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 14 to 70 percent. The magnitude and significance of the coefficient on the disaster variable, however, does not increase accordingly. In fact, the decreasing magnitude of disaster coefficients after 8 months suggests that there is indeed a temporal decay of the impact of disasters on SWB.

In model (2) we explicitly test the hypothesis of temporal decay. As results in table 5 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 first 2 months, 2-4 months and 4-6 months preceding the interview cannot be rejected. The coefficient becomes marginally insignificant (t=1.5) for events that occur within 6 to 8 months preceding the interview and dramatically drops in significance thereafter. This time window is consistent with the results in Table 4. Compared to previous studies, it is shorter than the 18 months considered

[6] All the regressions include individual characteristics and control for county fixed effects. This mitigates concerns about omitted variables bias unless the omitted variables vary over time. For example, because of general economic decline in the US during the late 2000s caused by the great recession, the negative association between the disaster and SWB might be spurious if disasters 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 fixed effect and year dummies, we repeated the regressions including the county level unemployment rate. The results were robust.

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 US was estimated to last only for two to three weeks after Hurricane Katrina.

[Table 5 about here]

Because most of the respondents are affected by at most one disaster during the previous 12 months, using the count of disasters in equation (3) instead of a dummy for occurrence of a disaster does not make a large difference in the results. The results for the disaster variable in Table 6 and Table 4 are quite similar, especially for shorter time horizons (albeit a bit smaller in Table 6). As the time window broadens, and the count of disasters grows, the coefficient on the number of disasters variable is statistically more significant than for the disaster dummy. An analysis of the temporal decay of the effects using non-overlapping, incremental time windows shows that events that occur within 6 to 8 months preceding the interview still have significant effect on SWB and that the decay starts within 8 to 10 months preceding the interview (results are not reported but available upon request).

[Table 6 about here]

Table (7) illustrates the different impacts of different disaster types on SWB. Results are reported for only two cumulative time windows of 8 and 12 months before the interview. We choose these two time windows because in the benchmark specification in Table 4, 8 months is the time window that, with the smallest BIC, produces the best fit, while 12 months is the maximum window length in the analysis.

[Table 7 about here]

Severe storms have a significant negative effect in both specifications based on both a disasters dummy and number of disasters variables, and a comparison between the coefficients for 8 and

12 months are consistent with a decay of their effect on SWB. 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 8 and 12 months. The point estimates in both cases are negative but they are statistically insignificant at the conventional levels. Floods, wildfires and freezes also exhibit insignificant coefficients. Droughts, on the other hand, show a negative effect on SWB that becomes statistically significant for a 12-month time window. 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 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). 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 US states throughout the whole year.

The damage specification models by disaster type are presented in table (8). In each column, each disaster is weighted by the damages it caused in terms of property (column 1), crops (column 2), number of deaths (column 3) and number of injured (column 4). Interestingly, although floods by themselves where marginally insignificant to explain life satisfaction in Table 7, they become statistically significant when weighted by their damages, especially in terms of the number of deaths and injured. The results suggest that severe storms are damaging to subjective well-being mainly through their associated property damages.

[Table 8 about here]

5. Discussion

The increase in weather and climate disasters in recent years has prompted an interest in analyzing the underlying reasons, consequences and required mitigation and adaptation measures. In this paper, we provide evidence of the effect of 42 billion-dollar disasters on the welfare of US residents between 2005 and 2010. We find that disasters reduce SWB (by approximately 0.0033 on a four-point scale) but that this effect decays with time and depends on the type of disaster.

Expanding the time interval between the event and the interview date may lead to find a significant effect of disasters, as it is found in previous studies. However, this should not necessarily be interpreted as a long lasting effect of disasters. In this study, we provide evidence that the effects of disasters on SWB decay after 6 to 8 months. By utilizing non-overlapping, incremental time periods in contrast to overlapping cumulative time periods, we find a quicker temporal decay of the effect of disasters than with cumulative expanded time periods. We show that the negative effects of disasters last for about 6 months, while with overlapping cumulative time windows, the effects appear to be significant until about 8 months.

During the period of study, severe storms appear to be the most influential disasters. Drought disasters take the the second place and tropical cyclones have only marginal negative effect only when the individual experiences more frequent tropical cyclone. Using the reported monetary damages based on insured losses, as an indicator for more destructive disasters, illustrates how intensity of tropical cyclone, severe storms and floods decrease individual SWB. Our results provide information on the relative importance of different disasters in term of intensity. They also suggest that despite the main goal of mandatory insurance (i.e. NFIP) to overcome the imperfections of private market insurance, flood disasters continue imposing negative impacts on individuals' SWB. Another explanation for the negative effect of flood property damage and crop damages on SWB, compared to other disaster types, is the accuracy of flood related data collection processes; National Weather Service (NWS) data preparers are required by The U.S Army Corps to record a monetary damage amounts for any flood events, while for other event types they can either report no information or give a rough estimation of damage costs.

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Table 1: Summary statistics of individual characteristics (BRFSS)

	Mean	Std. Dev.	Min	Max
Life satisfaction *(Ordered variable)*	3.39	0.63	1	4
Socio-demographic variables				
Education	14.06	2.13	0	16
Household Income (Categorical variable)				
Less than $10K	0.050	0.218	0	1
$10K- $15K	0.058	0.234	0	1
$15K-$20K	0.075	0.264	0	1
$20K-$25K	0.093	0.291	0	1
$25K- $35K	0.123	0.328	0	1
$35K- $50K	0.157	0.364	0	1
$50K-$75K	0.170	0.375	0	1
More than $75K	0.273	0.446	0	1
Marital Status (Categorical variable)				
Married	0.567	0.495	0	1
Divorced	0.145	0.352	0	1
Widowed	0.122	0.328	0	1
Separated	0.022	0.148	0	1
Never married	0.120	0.325	0	1
Cohabiting	0.023	0.150	0	1
Race (Categorical variable)				
White	0.835	0.371	0	1
Black or African American	0.090	0.286	0	1
Asian	0.018	0.131	0	1
Native Hawaiian/ Pacific Islander	0.002	0.045	0	1
American Indian/Alaskan Native	0.012	0.111	0	1
Other race	0.043	0.203	0	1
Age (Categorical variable)				
18 to 24	0.031	0.174	0	1
25 to 34	0.108	0.310	0	1
35 to 44	0.168	0.374	0	1
45 to 54	0.217	0.412	0	1
55 to 64	0.213	0.410	0	1
65 or older	0.263	0.440	0	1
Employment (Categorical variable)				
Employed for wages	0.478	0.500	0	1
Self-employed	0.084	0.278	0	1
Out of work for more than 1 year	0.020	0.139	0	1

Out of work for less that 1 year	0.025	0.156	0	1
Homemaker	0.071	0.257	0	1
Student	0.016	0.126	0	1
Retired	0.243	0.429	0	1
Unable to work	0.063	0.242	0	1
General health (Categorical variable)				
Poor	0.054	0.226	0	1
Fair	0.126	0.332	0	1
Good	0.299	0.458	0	1
Very good	0.332	0.471	0	1
Excellent	0.189	0.392	0	1
Sex (Dummy variable)				
Male	0.389	0.487	0	1

Table 2: 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 & 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 table 2 are based on direct insured and uninsured losses. Key data sources of quantified insured disaster loss data are the Insurance Services Office (ISO) Property Claim Services (PCS), Federal Emergency Management Agency (FEMA) National Flood Insurance Program (NFIP) and Presidential Disaster Declaration (PDD) assistance, and the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) & Risk Management Agency (RMA). (Smith and Katz, 2013). (c) Damage values represent the 2015 Consumer Price Index (CPI) cost adjusted values in billion dollars.

Table 3: Summary statistics of disaster variables (NCEI)

Variable	Mean	Std. Dev.	Min	Max
All disasters in cumulative and incremental time windows (number and dummy)				
Total number of disaster (2 months)	0.15	0.4	0	4
Total number of disaster (4 months)	0.31	0.57	0	4
Total number of disaster (6 months)	0.48	0.7	0	5
Total number of disaster (8 months)	0.66	0.79	0	5
Total number of disaster (10 months)	0.85	0.87	0	6
Total number of disaster (12 months)	1.03	0.94	0	7
Disaster (2 months)	0.14	0.35	0	1
Disaster (4 months)	0.27	0.44	0	1
Disaster (6 months)	0.39	0.49	0	1
Disaster (8 months)	0.50	0.50	0	1
Disaster (10 months)	0.61	0.49	0	1
Disaster (12 months)	0.70	0.46	0	1
Disaster (0-2)	0.14	0.35	0	1
Disaster (2-4)	0.14	0.35	0	1
Disaster (4-6)	0.15	0.36	0	1
Disaster (6-8)	0.16	0.36	0	1
Disaster (8-10)	0.17	0.38	0	1
Disaster (10-12)	0.17	0.37	0	1
Disasters by type in cumulative 8 and 12 month time windows (number and dummy)				
Number of tropical cyclone (8 months)	0.11	0.35	0	3
Number of tropical cyclone (12 months)	0.18	0.44	0	3
Number of severe storm (8 months)	0.3	0.58	0	4
Number of severe storm (12 months)	0.49	0.7	0	5
Number of flood (8 months)	0.05	0.22	0	1
Number of flood (12 months)	0.06	0.25	0	1
Number of drought (8 months)	0.12	0.34	0	2
Number of drought (12 months)	0.19	0.42	0	2
Number of wildfire (8 months)	0.04	0.19	0	1
Number of wildfire (12 months)	0.06	0.24	0	2
Number of freeze (8 months)	0.03	0.17	0	1
Number of freeze (12 months)	0.05	0.21	0	1
Tropical cyclone (8 months)	0.1	0.3	0	1
Tropical cyclone (12 months)	0.16	0.37	0	1
Severe storm (8 months)	0.25	0.43	0	1
Severe storm (12 months)	0.39	0.49	0	1
Flood (8 months)	0.05	0.22	0	1

Flood (12 months)	0.06	0.25	0	1
drought (8 months)	0.12	0.32	0	1
drought (12 months)	0.17	0.38	0	1
wildfire (8 months)	0.04	0.19	0	1
wildfire (12 months)	0.06	0.24	0	1
Freeze (8 months)	0.03	0.17	0	1
Freeze (12 months)	0.05	0.21	0	1
Disaster Damages (Million Dollars)[(a)]				
Tropical cyclone property damage	6.87	85.91	0.00	2,131.08
Tropical cyclone crop damage	1.00	15.61	0.00	423.00
Tropical cyclone deaths	0.13	3.15	0.00	166.00
Tropical cyclone injuries	2.87	80.90	0.00	2408.00
Severe storm property damage	1.77	22.37	0.00	1,010.67
Severe storm crop damage	0.10	2.79	0.00	250.55
Severe storm deaths	0.02	0.23	0.00	16.00
Severe storm injuries	0.23	2.92	0.00	150.00
Flood property damage	0.86	14.90	0.00	750.01
Flood crop damage	0.03	1.54	0.00	150.04
Flood deaths	0.01	0.21	0.00	11.00
Flood injuries	0.02	0.49	0.00	16.00
Drought property damage	0.00	0.20	0.00	100.00
Drought crop damage	0.48	16.21	0.00	710.20
Drought deaths	0.19	1.44	0.00	29.00
Drought injuries	2.10	33.06	0.00	1014.00
Wildfire property damage	0.12	6.38	0.00	500.08
Wildfire crop damage	0.00	0.38	0.00	77.00
Wildfire deaths	0.01	0.20	0.00	9.00
Wildfire injuries	0.13	1.50	0.00	36.00
Freeze property damage	0.00	0.03	0.00	0.85
Freeze crop damage	0.81	15.19	0.00	711.80
Freeze deaths	0.00	0.03	0.00	1.00
Freeze injuries	0.00	0.05	0.00	2.00

Note: (a)The storm event database by the National Weather Service (NWS) reports events in a county/zone basis. The estimated damage, deaths and injuries for counties that are part of a NWS forecast zone, reflect the physical and human loss associated with the total zone. (Table needs to be revised to reflect this).

Table 4: Effect of disaster on individual SWB across cumulative time windows

	(1)	(2)	(3)	(4)	(5)	(6)
k	2 months	4 months	6 months	8 months	10 months	12 months
Disaster(dummy)	**-0.00332****	**-0.00331*****	**-0.00357*****	**-0.00398*****	**-0.00284****	**-0.00225***
	(0.00151)	**(0.00127)**	**(0.00118)**	**(0.00116)**	**(0.00117)**	**(0.00117)**
Education	-0.03536***	-0.03536***	-0.03536***	-0.03534***	-0.03535***	-0.03535***
	(0.00242)	(0.00242)	(0.00242)	(0.00242)	(0.00242)	(0.00242)
Education^2	0.00134***	0.00134***	0.00134***	0.00134***	0.00134***	0.00134***
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Income (ref: Less than $10K)						
$10K-$15K	0.02660***	0.02660***	0.02660***	0.02660***	0.02659***	0.02659***
	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)
$15K-$20K	0.05580***	0.05580***	0.05580***	0.05580***	0.05579***	0.05580***
	(0.00376)	(0.00376)	(0.00376)	(0.00376)	(0.00376)	(0.00376)
$20K-$25K	0.06899***	0.06899***	0.06899***	0.06898***	0.06897***	0.06898***
	(0.00376)	(0.00376)	(0.00376)	(0.00376)	(0.00376)	(0.00376)
$25K-$35K	0.09517***	0.09518***	0.09517***	0.09517***	0.09516***	0.09517***
	(0.00375)	(0.00375)	(0.00375)	(0.00375)	(0.00375)	(0.00375)
$35K-$50K	0.13505***	0.13505***	0.13505***	0.13503***	0.13503***	0.13503***
	(0.00390)	(0.00390)	(0.00390)	(0.00390)	(0.00390)	(0.00390)
$50K-$75K	0.18719***	0.18719***	0.18719***	0.18718***	0.18717***	0.18718***
	(0.00420)	(0.00420)	(0.00420)	(0.00420)	(0.00420)	(0.00420)
More than $75K	0.26661***	0.26662***	0.26662***	0.26661***	0.26659***	0.26659***
	(0.00432)	(0.00432)	(0.00432)	(0.00432)	(0.00432)	(0.00432)
Marital Status (ref: Never married)						
Married	0.17009***	0.17008***	0.17008***	0.17009***	0.17009***	0.17009***
	(0.00221)	(0.00221)	(0.00221)	(0.00221)	(0.00221)	(0.00221)
Divorced	-0.00059	-0.00060	-0.00060	-0.00059	-0.00059	-0.00059
	(0.00264)	(0.00264)	(0.00264)	(0.00264)	(0.00264)	(0.00264)
Widowed	0.04805***	0.04804***	0.04805***	0.04805***	0.04805***	0.04805***
	(0.00280)	(0.00280)	(0.00280)	(0.00280)	(0.00280)	(0.00280)
Separated	-0.06725***	-0.06726***	-0.06726***	-0.06727***	-0.06727***	-0.06726***
	(0.00533)	(0.00532)	(0.00532)	(0.00532)	(0.00532)	(0.00533)
Cohabit	0.06616***	0.06616***	0.06615***	0.06616***	0.06615***	0.06616***
	(0.00425)	(0.00424)	(0.00424)	(0.00424)	(0.00424)	(0.00425)
Race (ref: White)						
Black/African American	0.05698***	0.05698***	0.05698***	0.05698***	0.05699***	0.05699***

	(0.00265)	(0.00266)	(0.00266)	(0.00265)	(0.00265)	(0.00265)
Asian	-0.02841***	-0.02842***	-0.02842***	-0.02843***	-0.02844***	-0.02843***
	(0.00460)	(0.00460)	(0.00460)	(0.00460)	(0.00460)	(0.00460)
Native Hawaiian / Pacific Islander	0.03170***	0.03167***	0.03163***	0.03160***	0.03162***	0.03162***
	(0.01134)	(0.01134)	(0.01135)	(0.01134)	(0.01134)	(0.01134)
American Indian/Native Alaskan	0.03441***	0.03442***	0.03443***	0.03443***	0.03442***	0.03442***
	(0.00544)	(0.00544)	(0.00544)	(0.00544)	(0.00544)	(0.00544)
Other	0.01873***	0.01873***	0.01871***	0.01868***	0.01869***	0.01871***
	(0.00387)	(0.00387)	(0.00387)	(0.00387)	(0.00387)	(0.00387)
Age (ref: 18-24)						
25 to 34	-0.06096***	-0.06096***	-0.06096***	-0.06094***	-0.06095***	-0.06095***
	(0.00354)	(0.00354)	(0.00354)	(0.00354)	(0.00354)	(0.00354)
35 to 44	-0.08555***	-0.08555***	-0.08554***	-0.08552***	-0.08553***	-0.08554***
	(0.00363)	(0.00363)	(0.00363)	(0.00363)	(0.00363)	(0.00363)
45 to 54	-0.07753***	-0.07753***	-0.07752***	-0.07750***	-0.07752***	-0.07752***
	(0.00361)	(0.00361)	(0.00361)	(0.00361)	(0.00361)	(0.00361)
55 to 64	-0.00020	-0.00020	-0.00019	-0.00017	-0.00019	-0.00020
	(0.00364)	(0.00363)	(0.00363)	(0.00364)	(0.00363)	(0.00364)
65 or older	0.08475***	0.08476***	0.08478***	0.08480***	0.08477***	0.08476***
	(0.00387)	(0.00387)	(0.00387)	(0.00387)	(0.00387)	(0.00387)
Employment (ref: employed for wages)						
Self-employed	0.00728***	0.00728***	0.00728***	0.00728***	0.00728***	0.00727***
	(0.00191)	(0.00191)	(0.00191)	(0.00191)	(0.00191)	(0.00191)
Unemployed-more than 1 year	-0.19207***	-0.19206***	-0.19206***	-0.19208***	-0.19209***	-0.19209***
	(0.00455)	(0.00455)	(0.00455)	(0.00455)	(0.00455)	(0.00455)
Unemployed-less that 1 year	-0.17456***	-0.17457***	-0.17456***	-0.17456***	-0.17454***	-0.17454***
	(0.00392)	(0.00392)	(0.00392)	(0.00392)	(0.00392)	(0.00392)
Homemaker	0.03472***	0.03472***	0.03473***	0.03472***	0.03471***	0.03472***
	(0.00218)	(0.00218)	(0.00218)	(0.00218)	(0.00218)	(0.00218)
Student	0.02036***	0.02035***	0.02034***	0.02034***	0.02035***	0.02035***
	(0.00476)	(0.00476)	(0.00477)	(0.00477)	(0.00477)	(0.00477)
Retired	0.05832***	0.05833***	0.05832***	0.05831***	0.05831***	0.05832***
	(0.00187)	(0.00187)	(0.00187)	(0.00187)	(0.00187)	(0.00187)
Unable to work	-0.14899***	-0.14899***	-0.14899***	-0.14899***	-0.14900***	-0.14900***
	(0.00364)	(0.00364)	(0.00364)	(0.00364)	(0.00364)	(0.00364)

General Health (ref: Poor)						
Fair	0.20621***	0.20621***	0.20621***	0.20622***	0.20621***	0.20622***
	(0.00355)	(0.00355)	(0.00355)	(0.00355)	(0.00355)	(0.00355)
Good	0.34168***	0.34167***	0.34168***	0.34169***	0.34168***	0.34169***
	(0.00345)	(0.00345)	(0.00345)	(0.00345)	(0.00345)	(0.00345)
Very good	0.50810***	0.50809***	0.50810***	0.50811***	0.50810***	0.50810***
	(0.00362)	(0.00362)	(0.00362)	(0.00362)	(0.00362)	(0.00362)
Excellent	0.64310***	0.64309***	0.64309***	0.64310***	0.64309***	0.64310***
	(0.00377)	(0.00377)	(0.00377)	(0.00377)	(0.00377)	(0.00377)
Male	-0.02363***	-0.02364***	-0.02363***	-0.02362***	-0.02362***	-0.02362***
	(0.00123)	(0.00123)	(0.00123)	(0.00123)	(0.00123)	(0.00123)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,273,963	1,273,963	1,273,963	1,273,963	1,273,963	1,273,963
Adjusted R-squared	0.1826	0.1826	0.1826	0.1826	0.1826	0.1826
BIC	-256314	-256317	-256319	-256322	-256316	-256313

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: Effect of disaster on individual SWB for incremental time windows

	(1)
Disaster (0 to 2 months)	-0.00410***
	(0.00154)
Disaster (2 to 4 months)	-0.00306**
	(0.00153)
Disaster (4 to 6 months)	-0.00418***
	(0.00145)
Disaster (6 to 8 months)	-0.00229
	(0.00153)
Disaster (8 to 10 months)	-0.00017
	(0.00149)
Disaster (10 to 12 months)	0.00019
	(0.00137)
Socio-demographic variables	Yes
County FE	Yes
Year dummies	Yes
Observations	1,273,963

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: Effect of disaster on individual SWB across cumulative time windows - Disaster frequency

k	(7) 2 months	(8) 4 months	(9) 6 months	(10) 8 months	(11) 10 months	(12) 12 months
Number of disasters	-0.00268**	-0.00288***	-0.00351***	-0.00359***	-0.00273***	-0.00239***
	(0.00131)	(0.00099)	(0.00082)	(0.00076)	(0.00073)	(0.00068)
Socio-demographic variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1273963	1273963	1273963	1273963	1273963	1273963

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: Effect of different type of disaster on individual life satisfaction

	(1)	(2)	(3)	(4)
k	8 months	12 months	8 months	12 months
	Dummy variable for occurrence of disaster		Number of disasters	
Tropical cyclone	-0.00229	-0.00229	-0.00253	-0.00231
	(0.00184)	(0.00167)	(0.00162)	(0.00140)
Severe storm	-0.00568***	-0.00215*	-0.00472***	-0.00234***
	(0.00130)	(0.00120)	(0.00097)	(0.00089)
Flood	-0.00405	-0.00337	-0.00372	-0.00322
	(0.00248)	(0.00253)	(0.00248)	(0.00252)
Drought	-0.00304	-0.00506***	-0.00303	-0.00385**
	(0.00194)	(0.00177)	(0.00185)	(0.00157)
Wildfire	-0.00022	0.00290	-0.00014	0.00307
	(0.00400)	(0.00338)	(0.00400)	(0.00326)
Freeze	-0.00050	-0.00112	-0.00076	-0.00172
	(0.00373)	(0.00309)	(0.00373)	(0.00309)
Socio-demographic variables	yes	yes	yes	yes
County FE	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Observations	1,273,963	1,273,963	1,273,963	1,273,963

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 8: Heterogeneous damage effect of disaster by types

	(1)	(2)	(3)	(4)
	(Disaster) × property damage	(Disaster) × crop damage	(Disaster) × #deaths	(Disaster) × #injuries
Tropical cyclone	-0.00001	-0.00005*	0.00007	-0.00000
	(0.00000)	(0.00003)	(0.00004)	(0.00000)
Severe Storm	-0.00004***	-0.00006	0.00020	-0.00032*
	(0.00001)	(0.00008)	(0.00317)	(0.00018)
Flood	-0.00005**	-0.00066*	-0.00497***	-0.00117***
	(0.00002)	(0.00036)	(0.00142)	(0.00027)
Drought	-0.00255***	0.00005***	-0.00084*	-0.00001
	(0.00031)	(0.00001)	(0.00046)	(0.00003)
Wildfire	0.00012**	0.00125	-0.00315	-0.00029
	(0.00005)	(0.00082)	(0.00456)	(0.00071)
Freeze	-0.00986	-0.00004	0.02832***	0.02607***
	(0.01870)	(0.00003)	(0.00509)	(0.00856)
Socio-demographic variables	yes	yes	yes	yes
County FE	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Observations	1,273,963	1,273,963	1,273,963	1,273,963

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