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Natural Hazard Risk and Life Satisfaction Empirical Evidence for U.S. Hurricanes

Michael Berlemann^{1,2,3}, Marina Eurich^{1*}

Abstract

The ongoing process of climate change goes along with an increase in the frequency and severity of various sorts of natural disasters. While the existing literature has almost exclusively focused on studying the direct effects resulting from different types of disasters, the effect of changing disaster risk so far has largely been neglected. In this paper we study the effect of hurricane risk on individual self-reported life satisfaction. In order to do so we combine geo-referenced survey data from the U.S. Gallup Daily Survey and hurricane data for the United States. Using Willoughby's (2006) wind field model we construct time-varying indicators of hurricane risk on the zip-code-level for the period of 2010 to 2018, based on historical hurricane data. We then study whether the time-varying hurricane risk indicators affect self-reported life satisfaction in a two-way fixed effects model. Our findings indicate that regions with comparatively high hurricane risk report significantly lower levels of life satisfaction than their counterparts in less hurricane-prone regions, even after controlling for zip-code-specific, time-specific and individual-specific differences. Thus, the impacts of natural disasters on life satisfaction tend to be underestimated when focusing on the direct effects exclusively.

Keywords

Hurricane risk — Life Satisfaction — Global Warming

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1. Introduction

The ongoing process of global warming, i.e. the upward trend of the average surface temperature since the early 20th century, and most notably since the late 1970s, goes along with an increase in the frequency and severity of various sorts of natural hazards. This holds true for temperature extremes (Rummukainen, 2012; Zhang et al., 2011) and heat waves (Schär et al., 2004; Jones et al., 2008; Kyseli, 2008), droughts (Dai, 2011), precipitation extremes (Lehmann et al., 2015), floods (Hirabayashi et al., 2013) and even storms (see e.g. Grinsted et al., 2012; Thomas, 2014). Against this background, economists have recently engaged in considerable attempts to quantify the costs of (climate-induced) natural disasters. Inspired by the early study of Skidmore and Toya (2002), most of the related literature focused on quantifying the growth effects of disaster events. While there is now little doubt that the short-term growth consequences of disasters are "naturally negative" (Felbermayr and Gröschl, 2014), the long-run effects are still somewhat controversial (Noy and duPont IV, 2018). However, recent empirical evidence points into the direction that disasters leave their traces in economic development even in the medium- and long-run (Hsiang and Jina, 2014; Berlemann and Wenzel, 2016; Berlemann and Wenzel, 2018).

often employed measure of material living standards, it is now widely accepted that purely consumption-based welfare indicators disregard important factors such as e.g. income distribution, personal security or environmental quality and thus should be complemented by more far-reaching indicators of societal progress. While various alternative concepts such as the Human Development Index (see e.g. McGillivray and White, 1993) or the Better Life Index (Durand, 2015) have been constructed for this purpose, self-reported measures of well-being (SWB) have established as the most comprehensive way of measuring societal welfare.¹ In order to gain a more complete picture of the effects of natural disasters on societal welfare a number of studies have recently studied whether and how natural disasters affect self-reported measures of well-being (see e.g. the study by Kimball et al. (2006) for Hurricane Katrina or Sapkota (2018) for the 2015 Nepal earthquake).² Typically these studies focus on the direct effects of a certain natural disaster on self-reported well-being. These direct effects might result from material losses of income and wealth or negative effects on the health status, e.g. when individuals suffered injuries in consequence of a disaster.

In this paper we extend the literature on the well-being effects of natural disasters by focusing on the effects of disaster

While (the growth of) per-capita GDP is surely the most

²We summarize this literature in more detail in Section 2 of this paper.

¹See Frey and Stutzer (2002).

risk rather than studying the well-being-effects of disasters themselves. We argue that the mere risk to be exposed to natural hazards might decrease self-reported well-being. In order to study this hypothesis we use geo-coded U.S. data from the Gallup Daily tracking survey over the period of 2010 to 2018 which also contain information on self-reported well-being. We combine the survey data with an indicator of time- and region-specific hurricane risk. To do so we impute geo-coded historical hurricane data into Willoughby's (2006) wind field model and aggregate the resulting data to our risk indicators.

Employing a two-way fixed effects panel estimation approach we in fact find significantly lower self-reported life satisfaction in regions with higher hurricane risk. This result turns out to be highly robust among various specifications and stability tests. Thus, the increase in the frequency or severity of climate-related natural disasters will likely not only cause more direct harm but also result in an additional decrease of life satisfaction due to higher perceived disaster risk.

The paper is structured as follows. Section 2 delivers an overview on the related literature. Section 3 explains our basic estimation approach and introduces the employed datasets. Section 4 delivers the estimation results for the effect of hurricane risk on self-reported well-being while Section 5 reports the results of a number of stability tests. Section 6 summarizes the main results and concludes.

2. Related Literature

The existing literature on the impact of natural disaster risk on self-reported measures of well-being is very small and developed in the context of the much larger literature on environmental valuation. Environmental economists have worked for long to develop valuation methods that can be used to generate reasonable estimates of monetary values of environmental amenities. A relatively new method is to asses the value of environmental goods (or bads) based on subjective well-being data. The well-being approach consists of regressing a measure of subjective well-being on a number of likely determinants (including income) and a measure of the environmental good to be evaluated. The value of the environmental good can then be assessed on the basis of the marginal rate of substitution between income and the level of the environmental good (see Welsch and Kühling, 2009). This approach has been applied to evaluate environmental quality (Van Praag and Baarsma, 2005; Ferreira and Moro, 2010) especially air pollution (Welsch, 2002; MacKerron and Mourato, 2009; Luechinger, 2009; Rehdanz and Maddison, 2008; Welsch, 2006), urban generation schemes (Dolan and Metcalf, 2008), and climate (Murray et al., 2013; Van de Vliert et al., 2004; Rehdanz and Maddison, 2005; Maddison and Rehdanz, 2011).

The well-being approach to environmental evaluation has also been applied to evaluate the costs of natural disasters. Besides, various studies have directly focused on the wellbeing effects of certain disasters or disaster types without the background of environmental evaluation. Various papers have studied the case of flood events.³ Luechinger and Raschky (2009) apply the valuation method to flood disasters in a sample of 16 European countries and find a significantly negative and robust effect on life satisfaction. However, the effect is quite short-lived and vanishes completely two years after the flood events occurred. von Möllendorff and Hirschfeld (2016) study the impact of five flood events on life satisfaction which occurred in between 2000 and 2011 in Germany. While the reported effects are somewhat smaller than those reported in Luechinger and Raschky (2009), they turn out to be significantly negative for up to 18 months. The study by Osberghaus and Kühling (2016), however, does not find an effect of flood experience of German households based on a cross-section survey for Germany conducted in 2012.

Kimball et al. (2006) were the first to study the effects of storm events on measures of self-reported well-being. The authors find a negative but very short-lived well-being-effect for individuals living close to the area affected by Hurricane Katrina in August 2005 in the United States. The analysis by von Möllendorff and Hirschfeld (2016) focuses on the impact of seven storm and hail events which occurred in between 2000 and 2011 in Germany. Even this study reports negative effects of storm events which are, however quite short-lived and diminish after 6 months. Similar results are reported in Ahmadiani and Ferreira (2016) for the U.S. Lohmann et al. (2019) study the well-being effects of storms for individuals living in Papua New Guinea. The authors report significantly negative but comparatively small effects of storm events. The study by Osberghaus and Kühling (2016) for Germany fails to find a well-being-effect for individuals which experienced storms.

Carroll et al. (2009) quantify the costs of droughts in Australia throughout the period of 2001 to 2004. They find that at least in rural areas life satisfaction significantly decreases during droughts. The study by Lohmann et al. (2019) also finds a negative well-being effect of droughts for the case of Papua New Guinea.

The case of forest fires has been analyzed by Kountouris and Remoundou (2011) for four Mediterranean European countries. The authors find life satisfaction of the rural population to be negatively affected. Ambrey et al. (2017) reports a similar result for bushfires in Australia.

Finally, even earthquakes have been investigated. Sapkota (2018) considers the effect of the 2015 Nepal earthquake based on survey data for 399 households. The author finds subjective well-being to be significantly negatively associated with the degree of experienced destruction.

To the best of our knowledge, up to now only two studies have touched upon the effect of disaster risk on self-reported measures of well-being. The study by Rehdanz et al. (2015)

³Among these studies is the one by Sekulova and van den Bergh (2016), which uses cross-section survey data from Bulgaria and reports negative life-satisfaction-effects of recently occurring flood events. However, as the survey was conducted with only flood-affected individuals, it is unclear in how far the results can be generalized.

is concerned with the earthquake close to the Japanese Pacific Coast in 2011, which finally led to the nuclear accident in Fukushima. Based on survey data the authors find that the survey respondents reported lower degrees of life satisfaction the closer they were living to Fukushima. Moreover, the authors studied whether the Fukushima disaster also triggered general concerns over nuclear power among those living close to other power plants. However, no such effect could be detected. Berlemann (2016) employs individual respondent data from three waves of the World Value Survey for more than 100 countries and constructs two alternative indicators of hurricane risk for the sample countries. When regressing happiness and life satisfaction on these indicators (and numerous control variables) the author finds a systematically negative effect of hurricane risk on both measures of individual well-being in relatively poor countries in which the population has little possibilities to take protective measures against storms. In highly developed countries the effect is much smaller and is significant only for life satisfaction.

We might conclude that systematic studies of the impact of disaster risk on self-reported measures of well-being are very rare. Moreover, the only two existing studies on this aspect deliver conflicting results. Our study contributes to filling this gap in the literature by delivering empirical evidence for the impact of hurricane risk on perceived well-being in the U.S. on the highly disaggregated zip-code level.

3. Estimation Approach and Data

3.1 Estimation Approach

Our aim is to explore whether hurricane risk has a systematic effect on individual well-being. In order to study this issue we follow a straight-forward empirical strategy. Basically, we regress self-reported measures of individual well-being from repeated cross-sections of an U.S.-wide survey on a set of individual control variables and a time- and region-varying measure of hurricane risk. Our estimation equation is thus

$$W_{i,j,t} = \alpha_j + \gamma_t + \theta X_{i,t} + \beta_1 \sum_{t}^{T} R_{j,t} + \varepsilon_{i,j,t}$$
(1)

with $W_{i,j,t}$ being a measure of well-being of individual *i* in region *j* at time *t*. The vector $X_{i,t}$ contains individual-level control variables, $R_{j,t}$ denotes the region- and time-specific hurricane risk and $\varepsilon_{i,j,t}$ captures the unexplained residual. In order to account for time-constant unobserved regional heterogeneity we estimate the model with region-fixed effects (α_j) and also account for time-specific unobserved heterogeneity by adding time-fixed effects γ_t .

Self-reported measures of well-being are typically measured on ordinal scales and, therefore, are often estimated using the methods of generalized linear models. However, as the inclusion of fixed effects is problematic in Ordered Logit or Probit models (Maddala, 1983), we estimate equation (1) using the ordinary least squares method. As Ferrer-i Carbonell and Frijters (2004) showed, assuming cardinality of well-being measures and using the OLS method rather than generalized linear models leads to very similar results and allows to control for fixed effects adequately.

Whenever we would be interested in the direct effect of hurricanes on self-reported measures of individual well-being we would have to take into account that at least some of the typically employed control variables might be highly correlated with the hurricane indicator. As an example, individuals affected by hurricanes might suffer injuries and therefore report lower health than before the hurricane. Similarly, hurricanes might affect the employment status, income and wealth. Whenever these variables are controlled for explicitly in the well-being regression, the effect of hurricanes would be underestimated. This "overcontrolling problem" is well documented in the related literature (Melissa Dell and Olken, 2014). However, in our estimation approach it is unlikely to occur as we are not interested in estimating the direct effect of hurricanes on self-reported well-being, but in the well-beingeffect of hurricane risk. Nevertheless, we also report results for a less restricted model without possibly endogenous controls (model 2).

3.2 Life Satisfaction Data

Our indicator of self-reported well-being comes from the Gallup Daily tracking survey. The survey, conducted by the Gallup Company since 2008, includes at least 1,000 U.S. adults each day, 350 days per year. The sample represents more than 95% of the U.S. adult population. A major advantage of the Gallup Daily tracking survey is that the data include zip-code information on the place of living of the respondents. It is thus possible to combine the survey data with other geo-coded datasets. As we explain in subsection 3.4 in more detail, we make use of this advantage by merging the Gallup data with hurricane data on the zip-code level. Moreover, when estimating equation (1) we code the regional fixed effect on the zip-code level.

Basically, Gallup Daily tracking consists of two parallel surveys: the U.S. Daily and the Gallup-Sharecare Well-Being Index, both of which have at least 500 respondents. The Gallup-Sharecare Well-Being Index focuses on an Americans' well-being. The Well-Being Index measures Americans' perceptions of their lives and their daily experiences through five interrelated elements that make up well-being: sense of purpose, social relationships, financial security, relationship to community, and physical health. Within the Gallup-Sharecare Well-Being Index survey the respondents are asked to report on their actual and future individual life satisfaction on a scale ranging from 0 to 10 (with 0 indicating the lowest possible life satisfaction and 10 the highest possible value). The questions to be answered are phrased

> "Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of

the ladder would you say you personally feel you stand at this time?"

and to rate their future life satisfaction

"On which step do you think you will stand about five years from now?"

We use the individual answers to the first question as cardinal measure of self-reported well-being as the main dependent variable in our subsequent empirical analysis.⁴ As outlined earlier, we use a two-way fixed effects panel model for our estimations. In order to be able to estimate the zip-code and time fixed effect accurately we only include data from zip-codes with at least 10 observations per year in our empirical analysis. Moreover, we restrict our analysis to zip-codes, which are exposed to at least minor hurricane risk. In order to identify these regions we make use of historical hurricane data for the period of 1851 to 2018.⁵ Figure 1 shows the mean reported life satisfaction for all 8,675 zip-codes included in our sample over the years 2010 to 2018.



Figure 1. Mean of 2010-2018 life satisfaction per zip-code

Altogether, we end up with 831,426 observations for the baseline regression and with 797,277 observations of prospective well-being (see Table 1).

Table 1. Summary statistics for life satisfaction

Statistic	Ν	Mean	St. Dev.	Min	Max
LS	831,426	7.06	1.88	0	10
Future LS	797,277	7.66	2.20	0	10

 $^{^{4}\}mathrm{The}$ answers to the second, prospective question are used in stability tests.

3.3 Control Variables

For our empirical analysis we need a broad set of control variables. All of these controls also come from the Gallup Daily tracking survey. Summary Statistics for the employed control variables can be found in Table (2). First, we make use of demographic information (e.g. gender, age, race, number of children living in the household). Our sampel is well-balanced between male and female respondents. Most of the individuals in the sample are white and married. Less individuals are either single/never been married, separated, divorced, widowed or in a domestic partnership/living with partner (not legally married). We also include information about the highest completed level of education which is categorized into "Less than a high school diploma", "High school graduate", "Technical, trade, vocational or business school or program after high school", "Some college", "Bachelor" and "(Some) postgraduate, professional schooling, professional degree". To consider health problems, which might impact life satisfaction, we add a dummy whether individuals have any health problems that prevent themselves from doing any of the things people at their age normally can do. Furthermore, we include a dummy for all unemployed individuals. We also include income information. As income is only available in classes we include dummies for each income class from less than \$720 up to \$120,000 or more.

Table 2. Summary statistics for control variables

Statistic	Mean	St. Dev.	Min	Max
Female	0.50	0.50	0	1
Age	52.86	17.74	18	99
White	0.78	0.41	0	1
Other Race	0.02	0.13	0	1
Black	0.11	0.31	0	1
Asian	0.02	0.14	0	1
Hispanic	0.07	0.26	0	1
Children	0.55	1.04	0	15
Single	0.19	0.39	0	1
Married	0.54	0.50	0	1
Separated	0.02	0.14	0	1
Divorced	0.12	0.32	0	1
Widowed	0.10	0.30	0	1
Partnership	0.04	0.20	0	1
Below High School	0.05	0.21	0	1
High School	0.19	0.39	0	1
Tech School	0.06	0.23	0	1
Some College	0.25	0.43	0	1
Bachelor	0.24	0.43	0	1
Post Grad	0.22	0.41	0	1
Low Health Status	0.22	0.42	0	1
Unemployed	0.06	0.23	0	1
Income	6.85	2.32	1	10
Observations	831,426			

 $^{^{5}}$ We explain the employed data and the exact sampling procedure in more detail in Section 3.4.

3.4 Hurricane Data and Risk Indicator

Hurricanes belong to the storm class of cyclones, which are defined as areas of low atmospheric pressure, characterized by rotating winds.⁶ Cyclones rotate counterclockwise in the Northern and clockwise in the Southern Hemisphere, which is due to the Coriolis effect. Depending on their region of origin, cyclones are classified as either tropical or extratropical. Tropical cyclones develop over warm water, mostly in between 5 and 20 degrees latitude. Extratropical cyclones have cool central cores as they typically form between 30 and 70 degrees latitude in combination with weather fronts. Both types of cyclones are highly destructive, although they differ in their source of energy and their structures. While tropical cyclones derive their energy from warm ocean water and heat of rising air which condenses and forms clouds, extratropical cyclones derive their energy from the temperature difference of airmasses on both sides of a weather front.

Tropical cyclones with a maximum sustained wind of 38 mph (61 km/h) or less are called "tropical depressions" (National Oceanic and Atmospheric Administration (NOAA)). Tropical cyclones reaching winds of at least 39 mph (63 km/h) are typically called "tropical storms" and are also assigned a name. If maximum sustained winds reach 74 mph (119 km/h), the cyclone is called a hurricane, whenever it developed in the North Atlantic Ocean, the Northeast Pacific Ocean east of the dateline or the South Pacific Ocean east of 160°E. In other regions the terms "typhoon" (Northwest Pacific Ocean west of the dateline), "severe tropical storm" (Southwest Pacific Ocean west of 160°E or Southeast Indian Ocean east of 90°E), and "severe cyclonic storm" (North Indian Ocean) are common. In the Southwest Indian Ocean the terminology sticks to the simple term "tropical cyclone".

Tropical cyclones are further classified according to their wind speed. This classification typically bases on the Saffir Simpson Scale (see Table 3).⁷ The Saffir Simpson Hurricane Wind Scale is a 1 to 5 rating based on hurricanes' intensities and soley focuses on the wind speed associated with a storm. It does not take into account the potential for other hurricane-related impacts such as storm surge and rainfallinduced floods. Earlier versions of this scale, known as the "Saffir Simpson Hurricane Scale", also incorporated these categories, however, often led to quite subjective and sometimes implausible categorizations of occurring storms. In order to reduce public confusion and to provide a more scientifically defensible scale, the storm surge ranges, flooding impact and central pressure statements were removed from the Saffir Simpson Scale and only peak winds are now employed.

The indicator of hurricane risk, we employ in our subsequent empirical analysis, is based on data from the "International Best Track Archive for Climate Stewardship (IB-TrACS)" dataset, provided by National Oceanic and Atmo-

spheric Administration. This dataset provides historical global data on the position of tropical cyclone centers in 3-hourly intervals in its geographic coordinates on a daily basis, measures of maximal sustained wind speed in knots from 1842 until today. We only include zip-codes in our sample with at least a minor risk of being hit by a hurricane. To distinguish between risk and no risk zip-codes we make use of the historical data on hurricanes and check whether zip-codes have ever been affected by a hurricane or not. Therefore, we construct a buffer of 480 km (300 miles) for each hurricane emerging until 2018 in the North Atlantic basin. 300 miles is the width from the center to which tropical storm-force winds can stretch out (Hurricane Basics, 1999) and has already been used in previous literature (see Batke et al., 2014). We then keep all zip-codes (n=8,675) within the buffer and include them into our subsequent empirical analysis.

The later employed hurricane indicator is based on the wind field model by Willoughby et al. (2006). This approach approximates wind profiles and overcomes the problem of earlier approaches which systematically overestimated maximum winds. In our application we make use of the R-package implemented by Anderson et al. (2020). The package needs a storms forward speed, the direction of forward motion, the gradient-level wind speed, the radius of maximum winds and the parameters for decay of winds away from the storm's center as inputs. The output consists of an approximation of the surface-level sustained wind for the geo-codes of interest. To illustrate the results, Figure 2 shows the estimated wind speeds of hurricane Katrina in 2005, one of the most destructive natural disasters which occurred in the United States.



Figure 2. Wind field model of hurricane Katrina

Our measure of hurricane risk is based on factual occurring hurricanes over the past. When constructing this indicator we have to take various factors into account. First, because

⁶The following expositions are primarily based on Keller and DeVecchio (2012) and Berlemann (2016).

⁷The scale is named after its inventors, the wind engineer Herb Saffir and the meteorologist Bob Simpson.

Category	Sustained Winds	Types of Damage Due to Hurricane Winds
1	74-95 mph 64-82 kt 119-153 km/h	Very dangerous winds will produce some damage: Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last a few to several days.
2	96-110 mph 83-95 kt 154-177 km/h	Extremely dangerous winds will cause extensive damage: Well-constructed frame homes could sustain major roof and siding damage. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks.
3	111-129 mph 96-112 kt 178-208 km/h	Devastating damage will occur: Well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.
4	130-156 mph 113-136 kt 209-251 km/h	Catastrophic damage will occur: Well-built framed homes can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Most trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
5	157 mph or higher 137 kt or higher 252 km/h or higher	Catastrophic damage will occur: A high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly or higher months. Most of the area will be uninhabitable for weeks or months.

Table 3. Saffir Simpson Hurricane Wind Scal

Source: http://www.nhc.noaa.gov/aboutsshws.php

hurricanes are rarely occurring events, we have to include many periods in the construction of our hurricane indicator. Second, as global warming itself has an impact on hurricane risk, the number of periods to be considered should not bee too large. Third, as we are not interested in the short-run effect of occurring hurricanes but, rather, want to identify only the effect of hurricanes risk, the indicator of hurricane risk should exclude the very recent past. In order to account for the first argument, we exclude all hurricanes from the calculation of hurricane risk, which occurred in the year before an individual was interviewed. As the previous literature showed, the effects of hurricanes on well-being turned out to be relatively short-lived. The number of periods to be included into the calculation of the hurricane risk indicator was chosen in line with the results presented in Berlemann (2016), who found the most systematic effects of hurricane risk on self-reported well-being for an evaluation period of 10 years.

For each respondent, included in our final sample, we calculate our measure of hurricane risk, which depends on the zip-code as well as on the interview date. As our sample covers the years 2010 to 2018, we employ hurricane data over the period of 1999 to 2017 for calculating the hurricane indicators. Figure 3 visualizes all hurricanes which occurred in the sample region over this period. As mentioned in Section 3.4, hurricanes tend to lose much of their wind intensities after



Figure 3. North Atlantic hurricanes 1999-2017, n=72

making landfall. Thus, in many cases the hurricanes shown in Figure 3 do not exceed the wind speed threshold of 74 mph (119 km/h) over the whole hurricane track. As only the sub-periods of excessive wind are destructive and dangerous, using the whole hurricane tracks would be misleading. In our



calculation of hurricane risk we only consider wind speeds exceeding the 74 mph (119 km/h) threshold and hence neglect wind speeds which are not characterized as a hurricane anymore. We illustrate this procedure again at the example of Hurricane Katrina. Figure 4 shows those wind speeds which exceeded the thresholds level for hurricanes. We show only those zip-codes which are part of our sample, i.e. for which we have at least 10 survey observations per sample year.

In total, 743 different zip-codes in our sample have been hit by at least one hurricane exceeding the threshold level (see Table 4). Some regions have been affected multiple times (13 zip-codes in our sample have been hit 4 times). Overall, the number of hurricane-affected zip-codes amounts to 1,102.

 Table 4. Number of affected zip-codes

Frequency	Count
1	492
2	156
3	82
4	13
Total	743

The majority of zip-codes (84.2%) has been hit by wind speeds belonging to hurricane category one. Much less have been affected by winds speeds of category two hurricanes (12.1%). Category three (3.1%) and category four hurricane wind speeds (0.6%) are already comparatively rare. Not a single zip-code was affected by wind speeds which would belong to a category five hurricane.

Figure 5 gives an overview on zip-codes which were severely affected by at least one hurricane over the period of 1999 to 2017. We also visualize how severely these zipcodes were affected over the entire period.

As explained earlier, we construct the hurricane risk indicator for each individual in our dataset separately, as even individuals living in the same zip-code might have been interviewed at different times. Whenever individuals were hit by excessive wind speeds various times over the evaluation period, we summarize the wind speeds of all relevant 10 years for this individual. Figure 6 summarizes the values of the resulting hurricane risk indicator by showing the mean values of the risk indicator over the entire sample period of 2010 to 2018 on the zip-code level.



Figure 5. Hurricane-affected sample zip-codes throughout 1999-2017

4. Estimation Results

Table 5 reports the regression results for the two-way fixed effects OLS estimation. In our baseline model (model 1) we estimate the effect of hurricane risk on life satisfaction using the earlier described risk indicator. Almost all controls have coefficients significantly different from zero which coincide with earlier findings in the literature (see e.g. Frey and Stutzer, 2002). Females exhibit higher levels of life satisfaction than males. Age has the typical U-shaped impact on life satisfaction. Also in line with the literature, we do not find an effect of children on life satisfaction (DiTella et al., 1999). Furthermore, married respondents as well as individuals living in partnerships report higher levels of life satisfaction, whereas separated, divorced and widowed respondents are less satisfied than singles. Low levels of education have a negative impact on life satisfaction while higher education levels go along with higher life satisfaction. Individuals reporting a low health level are less satisfied than more healthy individuals. The same holds true for unemployed respondents who report less levels of life satisfaction than their working counterparts. We also find a positive and significant impact of all income class dummies on life satisfaction (as compared to the lowest income class). In general the estimated marginal effects increase with the income class.

The estimated coefficient of our variable of central interest, the hurricane indicator, turns out to be negative and highly significant. Thus, higher levels of (perceived) hurricane risk go along with significantly lower life satisfaction. To clarify the magnitude of the estimated effect, we consider a hurricane



Figure 6. Mean of 2010-2018 risk indicator for all zip-codes

of size Katrina with wind speeds of max. 126.34 mph (203.33 km/h) and a mean of 84.31 mph (135.68 km/h) for affected zipcodes in our sample. A hurricane of this size would increase the hurricane risk indicator by max. 56.5 m/s (126.34 mph) for the most affected zip-code causing an average 0.11 decrease of life satisfaction and on an average by 37.69 m/s (84.31 mph) causing an average decrease of 0.07. Applying this logic to a hurricane of category 4 (average 63.89 m/s; 142.92 mph) results in a lower life satisfaction of 0.12.

As discussed earlier, some of the control variables might be endogenous (although this should, as also already discussed earlier, not be a major issue in our context). However, when excluding all possibly endogenous control variables and estimating the model only with gender, age and race controls as well as with two-way fixed effects we end up with very similar estimation results (model 2). Models (3)-(5) report results for variations of our hurricane risk indicator. In Model (3) we show the results we receive when including even lower wind speeds than 74 mph (119 km/h) in the construction of the risk indicator. As one would expect, the coefficient becomes somewhat smaller, but is still significant. Focusing exclusively on strong hurricanes, the effect increases in size. Models (4) and (5) provide results for risk indicators based on hurricanes with at least a maximum sustained wind speed of category two on the Saffir Simpson Hurricane Wind Scale (corresponds to 96 mph or 154 km/h) and at least a maximum sustained wind

speed of category three (111 mph or 178 km/h), respectively.

Altogether, our findings suggest that individuals living in regions with comparatively high hurricane risk report significantly lower levels of life satisfaction than their counterparts in less hurricane-prone regions, even after controlling for zip-code-specific, time-specific and individual-specific differences.

Baseline Val Controls All Storms Cal.2-s Cal.3-s n=831.426 n=1.068.887 n=831.426 n=831.426 Female 0.3067*** 0.1558*** 0.3054*** 0.0555*** 0.3055*** Age 0.0007) (0.0006) (0.0008) (0.0007) (0.0007) (0.0008) (0.0008) (0.0008) Age ² 0.0006*** 0.0006*** 0.0006*** 0.0006*** 0.0006*** (0.0006) Ohnood (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) Ohnood (0.0173) (0.0179) (0.0179) (0.0179) (0.0179) (0.0179) Black 0.213*** 0.0234* 0.0234* (0.0234* (0.0234* (0.0234* (0.0006) (0.0023) (0.0023) (0.0023) (0.0023) (0.0023) Marriad 0.2440*** 0.2448*** 0.2448*** 0.2448*** 0.2448*** (0.0100) (0.0167) (0.0179) (0.0179) (0.0167*						
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		Baseline	w/o Controls	All Storms	Cat.2-5	Cat.3-5
Female 0.305^{9+**} 0.305^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.3055^{9+**} 0.00041 (0.0041) (0.0041) (0.0041) (0.0041) (0.0041) (0.0041) (0.001) (0.0003) (0.0008) (0.0008) (0.0008) (0.0008) (0.0008) (0.0008) $(0.0006^{4***}$ 0.0006^{4***} 0.0006^{4***} $(0.0006^{4***}$ (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0006^{4***}) (0.0179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.179) (0.0179) (0.013) (0.013) $(0.013)^{4**}$ $(0.013)^{4***}$ $(0.013)^{4***}$ $(0.013)^{4***}$ $(0.013)^{4***}$ $(0.013)^{4***}$ $(0.0111)^{4***}$ $(0.0111)^{4***}$ $(0.0111)^{4***}$ $(0.0111)^{4***}$ $(0.012)^{2}$ $(0.002)^{2}$ $(0.0005)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0067)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ $(0.0167)^{2}$ <		n=831,426	n=1,068,887	n=831,426	n=831,426	n=831,426
Age (0.0041) (0.0041) (0.0041) (0.0041) (0.0041) Age^2 (0.007) (0.006) (0.0008) (0.0008) (0.0008) Age^2 (0.0006) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0000) (0.0017) (0.0173) (0.0173) (0.0179) (0.0179) (0.0179) (0.0173) (0.0167) (0.0173) (0.0173) (0.0173) (0.0173) $Back$ 0.2163^{***} -0.023^{**} -0.023^{**} -0.0234^{**} (0.0080) (0.0033) (0.0134) (0.0134) (0.0134) $Asian$ -0.0220^{**} 0.0237^{**} -0.0114^{***} -0.0114^{***} (0.0130) (0.0134) (0.0134) (0.0134) (0.0134) (0.0134) (0.0134) (0.0134) (0.0134) (0.0134) $Hispanic$ 0.319^{***} 0.0166^{***} (0.0134) (0.0134) (0.0023) (0.0023) (0.0023) (0.0023) (0.0023) $Married$ 0.2440^{***} 0.2440^{***} 0.2440^{***} 0.2440^{***} (0.0065) (0.0067) (0.0067) (0.0067) (0.007) (0.0077) (0.0077) (0.0077) (0.0084) (0.0086) (0.0086) (0.0086) (0.0083) (0.0086) (0.0086) (0.0086) (0.017) (0.0137) (0.0137) (0.0137) (0.018) $(0.$	Female	0.3067***	0.1558***	0.3054***	0.3055***	0.30551***
Age -0.0550*** -0.0254*** -0.0554*** -0.0534*** Age ² 0.0006*** 0.0008 (0.0008) (0.0008) Age ² 0.0006*** 0.0006*** 0.0006*** 0.0006*** Other Race 0.0173) (0.0167) (0.0179) (0.0179) Black 0.2163*** -0.0230 0.2136*** -0.0234* (0.0080) (0.0083) (0.0083) (0.0083) (0.0083) Asian -0.0220* 0.0237* -0.0234* -0.0234* (0.0096) (0.0096) (0.0099) (0.0033) (0.0023) Married 0.3195*** 0.3156*** 0.3155*** 0.3155*** (0.0022) (0.0023) (0.0023) (0.0023) Married 0.2440*** 0.2448*** 0.2448*** 0.2448*** (0.0079) (0.0185) (0.0185) (0.0185) Divorced -0.0924*** -0.0912*** -0.0912*** (0.0108) (0.0185) (0.0185) (0.0185) Divorced -0.09		(0.0040)	(0.0038)	(0.0041)	(0.0041)	(0.0041)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Age	-0.0550***	-0.0224***	-0.0554***	-0.0554***	-0.05539***
Age ² 0.000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0000^{***} 0.0130^{***} 0.0000^{***} 0.0130^{***} 0.0136^{***} 0.0136^{***} 0.0133^{***} 0.0023^{**} 0.0233^{***} 0.0023^{***} 0.0134^{***} 0.0134^{***} Asian -0.022^{0*} 0.0237^{**} -0.0234^{**} -0.0234^{**} -0.0234^{**} -0.0144^{***} $(0.0090)^{**}$ 0.0156^{***} 0.3155^{****} 0.3155^{****} 0.3155^{****} 0.3155^{****} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0116^{***} 0.0167^{*} 0.0023^{*} 0.0023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00023^{*} 0.00067^{*}		(0.0007)	(0.0006)	(0.0008)	(0.0008)	(0.0008)
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	Age ²	0.0006***	0.0003***	0.0006***	0.0006***	0.00064***
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Other Race	0.0418**	-0.1601***	0.0433**	0.0436**	0.04365**
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(0.0173)	(0.0167)	(0.0179)	(0.0179)	(0.0179)
Asian (0.0080) (0.0083) (0.0083) (0.0083) (0.0083) Asian -0.0220^{*} 0.0237^{*} -0.0234^{*} -0.0234^{*} -0.0234^{*} Hispanic 0.3193^{***} $0.01030)$ (0.0134) (0.0134) (0.0134) Hispanic 0.3193^{***} 0.0706^{***} 0.3155^{***} 0.3155^{***} 0.3155^{***} (0.0096) (0.0096) (0.0099) (0.0099) (0.0099) Children -0.0114^{***} -0.0116^{***} -0.0116^{***} (0.0022) (0.0023) (0.0023) (0.0023) Married 0.2440^{***} 0.2448^{***} 0.2448^{***} 0.2448^{***} (0.005) (0.0067) (0.0077) (0.0023) Separated -0.372^{***} -0.3464^{***} -0.3464^{***} (0.0179) (0.0185) (0.0185) (0.0185) Divorced -0.0924^{***} -0.0912^{***} -0.0912^{***} (0.0083) (0.0086) (0.0086) (0.0086) Widowed -0.0095 -0.0097 -0.0097 (0.0100) (0.0103) (0.0103) (0.0103) Partnership 0.043^{***} 0.0461^{***} 0.0461^{***} (0.0120) (0.0137) (0.0137) (0.0137) Tech School 0.0126 0.0182 0.0182 0.0182 (0.0130) (0.0137) (0.0137) (0.0137) Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} (0.0120) (0.0251) <	Black	0.2163***	-0.0020	0.2136***	0.2137***	0.21374***
Asian -0.0220^{*} 0.0237^{*} -0.0234^{*} -0.0234^{*} -0.0234^{*} -0.0234^{*} Hispanic 0.0130 (0.0130) (0.0134) (0.0134) (0.0134) Hispanic 0.0393^{***} 0.0706^{***} 0.3155^{***} 0.3155^{***} 0.3155^{***} Married 0.0022 (0.0099) (0.0023) (0.0023) (0.0023) Married 0.2440^{***} 0.2448^{***} 0.2448^{***} 0.2448^{***} 0.2448^{***} (0.0065) (0.0067) (0.0067) (0.0067) $0.0067)$ Separated -0.3472^{***} -0.3464^{***} -0.3464^{***} -0.3464^{***} (0.0179) (0.0185) (0.0185) (0.0185) (0.0185) Divorced -0.0924^{***} -0.0912^{***} -0.0912^{***} -0.0912^{***} (0.0103) (0.0103) (0.0185) (0.0185) (0.0185) Divorced 0.0095 (0.0086) (0.0086) (0.0086) Midowed (0.0126)		(0.0080)	(0.0083)	(0.0083)	(0.0083)	(0.0083)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Asian	-0.0220*	0.0237*	-0.0234*	-0.0234*	-0.02346*
Hispanic 0.3193^{***} 0.0706^{***} 0.3156^{***} 0.3155^{***} 0.31557^{***} Children 0.0096 (0.0096) (0.0099) (0.0099) (0.0099) (0.0099) Children -0.0114^{***} -0.0117^{***} -0.0116^{***} -0.0116^{***} (0.0023) (0.0023) (0.0023) (0.0023) Married 0.2440^{***} 0.2448^{***} 0.2448^{***} 0.2448^{***} (0.0065) (0.0067) (0.0067) (0.0067) Separated -0.3472^{***} -0.3464^{***} -0.3464^{***} (0.0179) (0.0185) (0.0185) (0.0185) Divorced -0.0924^{***} -0.0912^{***} -0.0912^{***} (0.0083) (0.0086) (0.0086) (0.0086) Widowed -0.0955 -0.0097 -0.00972 (0.0100) (0.0103) (0.0103) (0.0103) Partnership 0.0434^{***} 0.0461^{***} 0.0462^{***} 0.0461^{***} (0.0108) (0.0111) (0.0111) (0.0111) (0.0111) High School 0.0126 0.0182 0.0182 0.0182 (0.0120) (0.0135) (0.0137) (0.0137) (0.0137) Tech School $-0.0257*$ $-0.0257*$ $-0.0257*$ $-0.0257*$ (0.0130) (0.0135) (0.0135) (0.0135) Some College 0.1260^{***} 0.2691^{***} 0.2690^{***} (0.0130) (0.0137) (0.0137) (0.0137) Post Gra		(0.0130)	(0.0130)	(0.0134)	(0.0134)	(0.0134)
.(0.0096)(0.0096)(0.0099)(0.0099)(0.0099)Children -0.0114^{***} -0.0117^{***} -0.0116^{***} -0.0116^{***} (0.0022)(0.0023)(0.0023)(0.0023)Married 0.2440^{***} 0.2448^{***} 0.2448^{***} 0.2448^{***} (0.0065)(0.0067)(0.0067)(0.0067)Separated -0.3472^{***} -0.3464^{***} -0.3464^{***} (0.0179)(0.0185)(0.0185)(0.0185)Divorced -0.0924^{***} -0.0912^{***} -0.0912^{***} (0.0083)(0.0086)(0.0086)(0.0086)Widowed -0.0097 -0.0097 -0.0097 (0.0100)(0.013)(0.0103)(0.0103)Partnership(0.043^{***})(0.0182)(0.0182)(0.0126)(0.0182)(0.0182)(0.0182)(0.0126)(0.0127)(0.0137)(0.0137)Tech School -0.0798^{***} -0.0755^{***} -0.0754^{***} (0.0130)(0.0137)(0.0137)(0.0137)Some College 0.1260^{***} 0.1307^{**} 0.0257^{**} (0.0130)(0.0137)(0.0137)(0.0137)Post Grad 0.266^{***} 0.2691^{***} 0.2690^{***} (0.0133)(0.0137)(0.0137)(0.0137)Post Grad 0.2694^{***} 0.3073^{***} 0.3072^{***} (0.0251)(0.0055)(0.0055)(0.0055)Unemployed 0.3093^{***} 0.3038^{***} 0.3073^{***} <	Hispanic	0.3193***	0.0706***	0.3156***	0.3155***	0.31557***
$\begin{array}{llllllllllllllllllllllllllllllllllll$	1	(0.0096)	(0.0096)	(0.0099)	(0.0099)	(0.0099)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Children	-0.0114***		-0.0117***	-0.0116***	-0.01164***
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(0.0022)		(0.0023)	(0.0023)	(0.0023)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Married	0.2440***		0.2448***	0.2448***	0.24481***
$\begin{array}{llllllllllllllllllllllllllllllllllll$	mannea	(0.0065)		(0.0067)	(0.0067)	(0.0067)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Separated	-0 3472***		-0 3464***	-0 3464***	-0 34649***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Separated	(0.0179)		(0.0185)	(0.0185)	(0.0185)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Divorced	-0.0974***		-0.0912***	-0.0912***	-0.00120***
Widowed (0.0035)(0.0035)(0.0036)(0.0036)(0.0036)Partnership (0.0100)(0.0103)(0.0103)(0.0103)Partnership (0.0108)(0.0103)(0.0111)(0.0113)(0.0108)(0.0111)(0.0111)(0.0111)(0.0132)(0.0137)(0.0137)(0.0137)Tech School (0.0150)-0.0798***-0.0755***-0.0755***(0.0150)(0.0156)(0.0137)(0.0137)Tech School (0.0130)-0.0257*-0.0257*-0.02570*(0.0130)(0.0135)(0.0135)(0.0136)Bachelor (0.0132)0.1302***0.1301***0.13014***(0.0132)(0.0137)(0.0137)(0.0137)Post Grad (0.0133)0.2656***-0.7549***-0.7549***(0.0054)(0.0056)(0.0055)(0.0055)Unemployed (0.0054)-0.4838***-0.4839***-0.48372***(0.0261)(0.0271)(0.0271)(0.0271)Income Class 10.3093**0.1922***0.1922***0.1921***(0.0261)(0.0271)(0.0271)(0.0271)Income Class 30.2469***0.4653***0.4654***0.46550***(0.0242)(0.0251)(0.0251)(0.0251)Income Class 40.4698***0.4653***0.4654***0.46550***(0.0242)(0.0251)(0.0251)(0.0251)Income Class 50.6650***0.6612***0.6613***0.66136***(0.0242)(0.0251)(0.0251)(0.0251) <td>Divolceu</td> <td>(0.0924)</td> <td></td> <td>(0.0912)</td> <td>(0.0086)</td> <td>(0.0912)</td>	Divolceu	(0.0924)		(0.0912)	(0.0086)	(0.0912)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Widowed	0.0085		(0.0080)	(0.0080)	(0.0080)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	widowed	-0.0093		-0.0097	-0.0097	(0.0102)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Doutnoughin	(0.0100)		(0.0103)	(0.0103)	(0.0105) 0.04617***
High School (0.0108) (0.0111) (0.0111) (0.0111) (0.0111) High School 0.0126 0.0182 0.0182 0.0182 0.0182 (0.0132) (0.0137) (0.0137) (0.0137) (0.0137) Tech School $-0.0798**$ $-0.0755***$ $-0.0755***$ $-0.0755***$ (0.0150) (0.0156) (0.0156) (0.0156) Some College $-0.0310**$ $-0.0257*$ $-0.0257*$ $-0.0257*$ (0.0130) (0.0135) (0.0135) (0.0136) Bachelor $0.1260***$ $0.1302***$ $0.1301***$ $0.13014***$ (0.0132) (0.0137) (0.0137) (0.0137) Post Grad $0.2656***$ $0.2691***$ $0.2690***$ $0.26903***$ (0.0133) (0.0139) (0.0139) (0.0139) Low Health $-0.7566***$ $-0.7549***$ $-0.7549***$ (0.0054) (0.0056) (0.0055) (0.0055) Unemployed $-0.4821***$ $-0.4838***$ $-0.4839***$ (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 $0.3093***$ $0.3069***$ $0.3073***$ (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 $0.2469***$ $0.2448***$ $0.2449***$ (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 $0.4698***$ $0.4653***$ $0.6612***$ (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650	Partnership	(0.0434^{++++})		(0.0401^{+++})	(0.0402^{+++})	$(0.0401)^{4444}$
High School 0.0126 0.0182 0.0182 0.0182 0.0182 0.0182 0.0182 Tech School $-0.0798***$ $-0.0755***$ $-0.0755***$ $-0.0755***$ $-0.07549***$ (0.0150)(0.0156)(0.0156)(0.0156)(0.0156)Some College $-0.0310**$ $-0.0257*$ $-0.0257*$ $-0.02570*$ (0.0130)(0.0135)(0.0135)(0.0136)Bachelor $0.1260***$ $0.1302***$ $0.1301***$ $0.13014***$ (0.0132)(0.0137)(0.0137)(0.0137)(0.0137)Post Grad $0.2656***$ $0.2691***$ $0.2690***$ $0.26903***$ (0.0133)(0.0139)(0.0139)(0.0139)(0.0139)Low Health $-0.7566***$ $-0.7549***$ $-0.7549***$ $-0.75488***$ (0.0054)(0.0056)(0.0055)(0.0055)(0.0055)Unemployed $-0.4821***$ $-0.4838***$ $-0.48372***$ (0.0098)(0.0102)(0.0102)(0.0102)Income Class 1 $0.3093***$ $0.3069***$ $0.3073***$ (0.0261)(0.0271)(0.0271)(0.0271)Income Class 3 $0.2469***$ $0.4653***$ $0.4653***$ (0.0242)(0.0251)(0.0251)(0.0251)Income Class 5 $0.6613***$ $0.6613***$ (0.0242)(0.0252)(0.0251)(0.0251)Income Class 6 $0.8206***$ $0.8152***$ $0.8153***$ (0.0242)(0.0252)(0.0252)(0.0252)Income Class 6 $0.8206**$	III ah Cahaal	(0.0108)		(0.0111)	(0.0111)	(0.0111)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	High School	0.0126		0.0182	0.0182	0.01821
Tech School $-0.0/98^{***}$ $-0.0/55^{***}$ $-0.0/55^{***}$ $-0.0/54^{9***}$ (0.0150)(0.0156)(0.0156)(0.0156)(0.0156)Some College -0.0310^{**} -0.0257^{*} -0.0257^{*} -0.02570^{*} (0.0130)(0.0135)(0.0135)(0.0136)Bachelor 0.1260^{***} 0.1302^{***} 0.1301^{***} 0.13014^{***} (0.0132)(0.0137)(0.0137)(0.0137)(0.0137)Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} (0.0133)(0.0139)(0.0139)(0.0139)Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} (0.0054)(0.0056)(0.0055)(0.0055)Unemployed -0.4821^{***} -0.4838^{***} -0.4839^{***} (0.0098)(0.0102)(0.0102)(0.0102)Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} (0.0261)(0.0271)(0.0271)(0.0271)Income Class 3 0.2469^{***} 0.4653^{***} 0.4654^{***} (0.0242)(0.0251)(0.0251)(0.0251)Income Class 4 0.4698^{***} 0.4653^{***} 0.4651^{***} (0.0242)(0.0251)(0.0251)(0.0251)Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242)(0.0251)(0.0251)(0.0251)Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242)(0.0252)(0	TE 1 C 1 1	(0.0132)		(0.0137)	(0.0137)	(0.0137)
	Tech School	-0.0/98***		-0.0/55***	-0.0/55***	-0.0/549***
Some College -0.0310^{**} -0.0257^{*} -0.0257^{*} -0.0257^{*} -0.0257^{*} Bachelor 0.1260^{***} (0.0135) (0.0135) (0.0136) Bachelor 0.1260^{***} 0.1302^{***} 0.1301^{***} 0.1301^{***} (0.0132) (0.0137) (0.0137) (0.0137) (0.0137) Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} (0.0133) (0.0139) (0.0139) (0.0139) Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} (0.0054) (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.4839^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.469^{***} 0.4653^{***} 0.4653^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.6612^{***} 0.6613^{***} 0.6613^{***}	a a 11	(0.0150)		(0.0156)	(0.0156)	(0.0156)
Bachelor (0.0130) (0.0135) (0.0135) (0.0136) Bachelor 0.1260^{***} 0.1302^{***} 0.1301^{***} 0.13014^{***} (0.0132) (0.0137) (0.0137) (0.0137) (0.0137) Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} (0.0133) (0.0139) (0.0139) (0.0139) Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} (0.0054) (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.4839^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} (0.0242) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.4654^{***} (0.0242) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***}	Some College	-0.0310**		-0.0257*	-0.0257*	-0.02570*
Bachelor 0.1260^{***} 0.1302^{***} 0.1301^{***} 0.13014^{***} (0.0132) (0.0137) (0.0137) (0.0137) (0.0137) Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} (0.0133) (0.0139) (0.0139) (0.0139) Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} (0.0054) (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.48372^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} (0.0326) (0.0338) (0.0338) (0.0338) Income Class 2 0.1896^{***} 0.1922^{***} 0.19231^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.4653^{***} 0.46550^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.81541^{***}	~	(0.0130)		(0.0135)	(0.0135)	(0.0136)
Post Grad (0.0132) (0.0137) (0.0137) (0.0137) Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} (0.0133) (0.0139) (0.0139) (0.0139) Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} (0.0054) (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.48372^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} (0.0326) (0.0338) (0.0338) (0.0338) Income Class 2 0.1896^{***} 0.1922^{***} 0.1922^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.4654^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.81541^{***}	Bachelor	0.1260***		0.1302***	0.1301***	0.13014***
Post Grad 0.2656^{***} 0.2691^{***} 0.2690^{***} 0.2690^{***} 0.2690^{***} Low Health -0.7566^{***} (0.0139) (0.0139) (0.0139) Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} -0.7548^{***} (0.0054) (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.4839^{***} -0.48372^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} 0.30724^{***} (0.0326) (0.0338) (0.0338) (0.0338) Income Class 2 0.1896^{***} 0.1922^{***} 0.1922^{***} 0.19231^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} 0.24500^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.46550^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***}		(0.0132)		(0.0137)	(0.0137)	(0.0137)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Post Grad	0.2656***		0.2691***	0.2690***	0.26903***
Low Health -0.7566^{***} -0.7549^{***} -0.7549^{***} -0.7548^{***} Unemployed -0.4821^{***} (0.0056) (0.0055) (0.0055) Unemployed -0.4821^{***} -0.4838^{***} -0.4839^{***} -0.48372^{***} (0.0098) (0.0102) (0.0102) (0.0102) Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} 0.30724^{***} (0.0326) (0.0338) (0.0338) (0.0338) Income Class 2 0.1896^{***} 0.1922^{***} 0.1922^{***} 0.19231^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} 0.24500^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.4654^{***} 0.46550^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.81541^{***}		(0.0133)		(0.0139)	(0.0139)	(0.0139)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Low Health	-0.7566***		-0.7549***	-0.7549***	-0.75488***
Unemployed (0.0098) -0.4839^{***} (0.0098) -0.4839^{***} (0.0102) -0.48372^{***} (0.0102) Income Class 1 0.3093^{***} 		(0.0054)		(0.0056)	(0.0055)	(0.0055)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Unemployed	-0.4821***		-0.4838***	-0.4839***	-0.48372***
Income Class 1 0.3093^{***} 0.3069^{***} 0.3073^{***} 0.30724^{***} (0.0326) (0.0338) (0.0338) (0.0338) (0.0338) Income Class 2 0.1896^{***} 0.1922^{***} 0.1922^{***} 0.1923^{***} (0.0261) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} 0.24500^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.4654^{***} 0.46550^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.81541^{***}		(0.0098)		(0.0102)	(0.0102)	(0.0102)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Income Class 1	0.3093***		0.3069***	0.3073***	0.30724***
Income Class 2 0.1896^{***} 0.1922^{***} 0.1922^{***} 0.19231^{***} (0.0261) (0.0271) (0.0271) (0.0271) (0.0271) Income Class 3 0.2469^{***} 0.2448^{***} 0.2449^{***} 0.24500^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 4 0.4698^{***} 0.4653^{***} 0.4654^{***} 0.46550^{***} (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650^{***} 0.6612^{***} 0.6613^{***} (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206^{***} 0.8152^{***} 0.8153^{***} 0.81541^{***}		(0.0326)		(0.0338)	(0.0338)	(0.0338)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Income Class 2	0.1896***		0.1922***	0.1922***	0.19231***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0261)		(0.0271)	(0.0271)	(0.0271)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Income Class 3	0.2469***		0.2448***	0.2449***	0.24500***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0242)		(0.0251)	(0.0251)	(0.0251)
Income Class 5 (0.0242) (0.0251) (0.0251) (0.0251) Income Class 5 0.6650*** 0.6612*** 0.6613*** 0.66136*** Income Class 6 0.8206*** 0.8152*** 0.8153*** 0.81541***	Income Class 4	0.4698***		0.4653***	0.4654***	0.46550***
Income Class 5 0.6650*** 0.6612*** 0.6613*** 0.66136*** (0.0242) (0.0252) (0.0252) (0.0252) Income Class 6 0.8206*** 0.8152*** 0.8153*** 0.81541***		(0.0242)		(0.0251)	(0.0251)	(0.0251)
(0.0242)(0.0252)(0.0252)(0.0252)Income Class 60.8206***0.8152***0.8153***0.81541***	Income Class 5	0.6650***		0.6612***	0.6613***	0.66136***
Income Class 6 0.8206*** 0.8152*** 0.8153*** 0.81541***		(0.0242)		(0.0252)	(0.0252)	(0.0252)
	Income Class 6	0.8206***		0.8152***	0.8153***	0.81541***

Table 5. Two-way fixed effects results for life satisfaction on hurricane risk

Continued on next page

	Baseline	w/o Controls	All Storms	Cat.2-5	Cat.3-5
	n=831,426	n=1,068,887	n=831,426	n=831,426	n=831,426
	(0.0244)		(0.0254)	(0.0254)	(0.0254)
Income Class 7	0.9819***		0.9761***	0.9761***	0.97621***
	(0.0242)		(0.0251)	(0.0251)	(0.0251)
Income Class 8	1.1396***		1.1345***	1.1346***	1.13471***
	(0.0245)		(0.0254)	(0.0254)	(0.0254)
Income Class 9	1.3384***		1.3326***	1.3326***	1.33267***
	(0.0242)		(0.0252)	(0.0252)	(0.0252)
Hurricane Risk	-0.0019***	-0.0016***	-0.0006***	-0.0035***	-0.00316*
	(0.0004)	(0.0004)	(0.0001)	(0.0009)	(0.0018)

Table 5 – *Continued from previous page*

Notes: All specifications include zip-code and year fixed effects. Standard errors (in parentheses) clustered at the zip-code level. *p<0.1; **p<0.05; ***p<0.01

5. Stability Tests

To further substantiate our results, we conducted various stability tests. In the following we report and discuss their results.

In a first stability test, we check the effect of changing the length of the window we employ to calculate hurricane risk. We reduce the number of included periods stepwise to 7 and increase it stepwise until 13. For all these specifications the estimated coefficients of the hurricane indicator remains negative and turns out to be highly significant. Including more years even leads to an increase in the size of the coefficient which means we find an even higher effect of hurricane risk on life satisfaction.⁸

As a second stability test, we raise the minimum number of observations necessary per sample year to be included into the estimation. As explained earlier in 3.2 we only included zip-codes into the analysis for which we have at least 10 observations per year to be able to estimate the fixed effect accurately. When we increase this threshold to 20 observations per year, the number of observations roughly reduces to half of those included in the baseline estimations. As the first column of Table 6 shows, the effect of the hurricane indicator becomes slightly smaller, but is still negative and highly significant.

In order to rule out that our results are driven by the direct effects of hurricanes rather than by disaster risk, we conduct a third stability test. In addition to dropping the hurricanes which occurred in the year before the respondents were surveyed when calculating our hurricane risk indicator we also drop all observations from zip-codes which intersect with the core storm tracks. Most likely the most severe damages were caused on these storms tracks so that we end up with a highly conservative estimator when excluding these observations. The results are reported in column three of Table 6. Again, the results turn out to be stable.

Finally, we repeated the estimations with expected future life satisfaction as right-hand variable. This variant thus considers the forward-looking aspect of life satisfaction. The estimation results, which are shown in column three of Table 6, again are very similar as in the baseline regression.

Table 6. Stability Tests Life Satisfaction and Hurricane Risk

 (Two-way FE OLS)

•			
	20 O/Yr/ZIP	Non-hit ZIPs	Future LS
	n=437,172	n=676,280	n=797,277
Hurricane Risk	-0.0012*	-0.0013***	-0.0017***
	(7e-04)	(5e-04)	(5e-04)
Controls included	Yes	Yes	Yes

Notes:

All specifications include zip-code and year fixed effects. Standard errors in parentheses clustered at the zip-code level. *p<0.1; **p<0.05; ***p<0.01

6. Summary and Conclusions

Most scientists expect global warming to continue for the foreseeable future even if the climate goals of the Paris agreement of 2015 were to be met. Thus, a further increase in the frequency and the severity of climate-related natural hazards is very likely. Against this background, further research on the effects of increasing natural hazard risk is urgently necessary.

In this paper we contribute to this literature by delivering an analysis of the well-being effects of disaster risk. At the example of the United States we show that an increase in hurricane risk goes along with a significant and sizeable decrease of life satisfaction. Thus, living under increasingly uncertain conditions has a detrimental effect on individual well-being, even when many individuals never experience a natural disaster themselves. Hence, the negative effects of climate-induced natural disasters go well beyond the negative effects of the directly affected individuals.

⁸The full estimation results are available from the authors on request.

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