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Hurricane Risk, Happiness and Life Satisfaction. Some Empirical Evidence on the Indirect Effects of Natural Disasters

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Hurricane Risk, Happiness and Life Satisfaction

Some Empirical Evidence on the Indirect Effects of Natural Disasters

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As a consequence of climate change, certain types of natural disasters become either more likely or more severe. While disasters might have numerous direct (typically negative) effects, the effect of an increase of natural disaster risk on individual well-being is often neglected. In this paper we study the effects of natural disaster risk on self-reported happiness and life satisfaction at the example of tropical storms. Combining several waves of the World Values Survey and appropriate storm data we find that disaster risk tends to have little systematic effect on self-reported happiness, once we correct for individual characteristics. However, hurricane risk turns out to decrease life satisfaction significantly. We conclude that when individuals evaluate their long-term satisfaction with their life, disaster risk is perceived as threat to individual well-being.

Keywords: Happiness; Life Satisfaction; Well-Being; Natural Disasters

JEL classification: I31,Q54

1 Introduction

The world has seen many natural disasters over the years. Some of the worst disasters such as the earthquake in Syria of 1202 with a death toll of more than a million are documented in our history books. Others made it even to the classic literature, such as the destruction of Pompeji in consequence of the eruption of the Vesuv volcano in 79 a.D., which became the central topic of Friedrich Schiller's elegy of 1796 "Pompeji and Herkulaneum". Nowadays, more systematic records of natural disasters are available. For week 28 of 2014, when the introduction to this paper was written, the disaster database EMDAT[1] reports three natural disasters: an earthquake in the San Marcos department (Guatemala), the typhoon Neoguri in Japan and floods and landslides in the Cote d'Ivoire. The various types of natural disasters occur in almost all countries around the globe, however with differing intensities and in differing frequencies.

Although natural disasters have affected human well-being ever since, for long periods of time the economic effects of natural disasters have been unexplored. Throughout the last decade, research on the economic effects of natural disasters has been intensified as a consequence of the rising interest in the process of global warming. The term "global warming" refers to the phenomenon of increasing average surface temperatures.[2] According to the Intergovernmental Panel on Climate Change (IPCC) global average surface temperature increased in the interval between 1880 and 2012 by approximately 0.9°C. The prevailing opinion among scientists is that human activities contributed considerably to global warming, especially by burning fossil fuel, thereby increasing the concentration of greenhouse gases in the atmosphere (Intergovernmental Panel on Climate Change, 2013). Moreover, the process of global warming is expected to continue even under the assumption of massive reductions in future emissions (see e.g. Solomon et al., 2009). The rise of global temperatures is responsible for a broad range of changes, among them a rising sea level (Cazenave and Nerem, 2004), species extinctions and the spread of diseases (e.g. Malaria) to more regions. Moreover, global warming likely will affect the frequency and/or the severity of certain types of natural disasters, among them floods (Milly et al., 2002) and hurricanes (Hoyos et al., 2006).[3] Against this background, scientific interest in the effects of natural disasters has increased considerably.

Most of the research on the effects of natural disasters has focused on the question of the short- and medium-term growth effects of natural disasters and is empirical

[1]See http://www.emdat.be .

[2]Global warming is related to the more general phenomenon of climate change, which refers to changes in the the sum of all attributes defining climate, among them surface temperatures, but also precipitation patterns, winds and ocean currents.

[3]See also van Aalst (2006) for a discussion of the interdependence between climate change and natural disasters.

in nature. The literature on short-term effects of natural disasters typically finds that disasters tend to have negative effects in the very short-run which turn into positive effects soon thereafter.[4] While studies with longer time-horizons are recently gaining more interest, they are still relatively rare and failed to deliver consistent results.[5]

Only recently, the economic literature has considered that the effects of natural disasters might go well beyond the issue of macroeconomic growth. Natural disasters might affect an individual's well-being through a direct and an indirect channel. Natural disasters might directly affect an individual's health or employment status, individual wealth or income. All these factors have found to be significant determinants of subjective measures of self-reported individual well-being (see, e.g., Frey and Stutzer, 2002). Thus, individuals losing their jobs, getting injured, losing wealth or income in the consequence of an occurring natural disaster will likely report lower life satisfaction and/or happiness because their living conditions are directly affected by disasters. However, natural disasters might also affect individual well-being through a more indirect channel. The mere possibility that natural disasters might occur and affect individual living conditions might be an additional source of individual disutility. If this holds true, high disaster risk should go along with low self-reported well-being.

Interestingly enough, the question whether disaster risk has a significant effect on self-reported well-being has rarely been touched upon. Most of the few related papers are concerned with the direct effect of certain disasters and not with disaster risk in a more general sense. A first strand of this small literature uses happiness or life satisfaction data to evaluate the true losses from disasters. While parts of this literature are more generally concerned with the effects of environmental quality or climate on well-being (e.g. Welsch, 2002, Rehdanz and Maddison, 2008, Luechinger, 2009, Rehdanz and Maddison, 2011), some recent papers are explicitly concerned with (certain types of) natural disasters (Luechinger and Raschky, 2009, Carroll, Frijters and Shields, 2009). A second strand of the literature focuses more directly on the effects of certain natural disasters on subjective well-being (Kimball et al., 2006, Berger, 2010, Yamamura, 2012).[6]

In this paper we contribute to filling the described gap in the literature by studying whether the perceived risk from hurricanes, a specific and highly destructive form of storms which can occur in many regions around the globe, has a systematic effect on individual well-being. Based on three waves of the integrated European/World Values Survey we run a series of pooled ordered logit regressions to study whether the perceived risk of severe tropical storms has a significant impact on happiness and/or life satisfaction. As the integrated European/World Values Survey itself contains no

[4]See, e.g., Albala-Bertrand (1993), ECLAC (2000), Chavériat (2000), Rasmussen (2004), Raddatz (2007), Berlemann and Vogt (2008), Heger, Julca and Paddison (2008), Noy (2009), Fomby, Ikeda and Loayza (2013).

[5]See e.g. Skidmore and Toya (2002), Cuaresma, Hlouskova and Obersteiner (2008), Jaramillo (2007).

[6]In Section 2 we summarize this literature in more detail.

information on perceived hurricane risk, we add measures of hurricane risk derived from a meteorological database to the dataset, thereby assuming that respondents to the surveys base their risk assessment on hurricanes which occurred in the past. In order to construct appropriate hurricane risk indicators we make use of the Best Track Dataset of tropical cyclones jointly provided by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center and the Oceanography Center / Joint Typhoon Warning Center.[7] Based on this dataset we calculate both, a frequency and a severity indicator of hurricane risk on an annual basis. As we have little information on how many years individuals take into account in their assessment of hurricane risk, we allow for a wide range of alternative specifications. Based on our estimation results we conclude that the contemporaneous dimension of well-being, self-reported happiness, shows little systematic relation to our measures of perceived disaster risk. If at all, happiness reacts to hurricane events which occurred in the very recent past. However, we find strong empirical support for the hypothesis that life satisfaction as the more long-term oriented component of well-being is affected negatively by perceived hurricane risk.

The paper is organized as follows: Section 2 delivers an overview on the literature studying the effects of natural disasters on happiness or life-satisfaction. The 3rd section introduces the employed data and delivers some summary statistics. Section 4 outlines the estimation approach and delivers the results of our baseline regressions. Section 5 deals with the effect of hurricane risk on happiness, section 6 delivers the results for life satisfaction. Section 7 summarizes the main results and draws some conclusions.

2 Related Literature

The empirical literature related to this paper evolved out of the broad strand of literature on the determinants of happiness and life satisfaction.[8] Although the terms happiness and life satisfaction are often used interchangeably, the two concepts do not coincide. However, both are related and can be thought of as elements of subjective well-being, i.e. "a state of stable, global judgment of life quality and the degree to which people evaluate the overall quality of their lives positively" (Yang, 2008, p. 204.). While especially the concept of happiness is quite controversial and not equally defined across all disciplines concerned with happiness, most will agree that happiness is a subjective, positive, and inner psychological state of mind (Tsou and Liou, 2001). However, no consensus is yet reached on the issue whether happiness is a measure of emotion, of thought or even both (Crooker and Near, 1998). However, according to both interpretations happiness refers

[7]We provide a more detailed description of the data sources in the data section.

[8]For reviews of this literature see Frey and Stutzer (2002), van Praag and Ferrer-I-Carbonell (2004), Frey (2008) or Diener and Biswas-Diener (2008).

to the comparatively short-term and more volatile component of individual well-being. The concept of life satisfaction is much less controversial. Life satisfaction generally refers to the summation of evaluations regarding a person's life as a whole. Most researchers agree that measures of life satisfaction are cognitive (Crooker and Near, 1998). Life satisfaction can be thought of as the less volatile long-term component of individual well-being.

Previous research on happiness and life satisfaction has identified a number of significant determinants of subjective well-being.[9] Various individual characteristics have found to play a systematic role in explaining subjective well-being such as age, marriage, the health status and disabilities. The results for other individual factors such as gender, having children and education are less clear-cut.[10] Economic factors such as individual unemployment and income have also often been studied. While unemployment and job dissatisfaction reduce subjective well-being, the effect of income is highly controversial. Easterlin (1974) reported the peculiar finding that income and happiness are positively correlated within the cross-section- but not in the time-dimension, a finding which is often referred to as "Easterlin Paradox" (see also Easterlin, 1995). However, this result has often been challenged (see, e.g., Hagerty and Veenhoven, 2003, Stevenson and Wolfers, 2008).

Empirical studies of the influence of natural disasters on subjective well-being have been conducted only recently. As outlined earlier, this yet comparatively small literature can be subdivided into two groups.

A first group of papers evolved within the literature on environmental evaluation. As an alternative to the conventional methods (such as contingent valuation, travel cost models and hedonic approaches) the value of environmental goods (or bads) can be assessed using subjective well-being data. The idea behind this approach[11] is to regress a measure of subjective well-being on a number of likely determinants (including personal 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 rate of marginal substitution between income and the level of the environmental good. This approach has been used to assess the value of environmental quality (Welsch, 2002, van Praag and Baarsma, 2005, Welsch, 2006, Rehdanz and Maddison, 2008, MacKerron and Mourato, 2009, Luechinger, 2009, Ferreira and Moro, 2010), urban regeneration schemes (Dolan and Metcalfe, 2008) and climate (Van der Vliert et al., 2004, Rehdanz and Maddison, 2005, Maddison and Rehdanz, 2011). Two papers yet applied the approach to the evaluation of natural disasters. Carroll, Frijters and Shields (2009) made an attempt at quantifying the costs of droughts in Australia throughout the period of 2001 to

[9] A comprehensive summary of the main findings can e.g. be found in Frey and Stutzer (2002).

[10] See, e.g. Frijters, Haisken-DeNew and Shields (2004).

[11] For a detailed overview on the approach see, e.g., Welsch and Kühling (2009).

2004. They find that at least in rural areas life satisfaction significantly decreases during droughts. Luechinger and Raschky (2009) apply the valuation method to flood disasters in a sample of 15 European countries and find a significant negative and robust effect on life satisfaction. The effect starts to decay one year after the disasters occurred and completely vanishes after two years.

The second group of papers makes no attempt of monetizing the effect of disasters but directly focuses on the effects of disasters on economic well-being. Three papers belong into this group.

First, Kimball et al. (2006) use happiness data from the University of Michigan Consumer Survey to study the effects of two natural disasters. For the period of August to October 2005 the Michigan Survey included questions on happiness. For this period weekly data is available. The authors use the dataset to study the reaction of the respondents to two natural disasters which occurred throughout the sample period. The first disaster was Hurricane Katrina in August 2005, the second one a large earthquake in Pakistan in October 2005. The authors report a decrease in happiness in early September which lasted for 2-3 weeks and which was most pronounced in the South Central region which was closest to the devastation of Katrina. The authors also found happiness to decrease after the Pakistan earthquake, thereby indicating that the respondents did not only care about disasters in their own country but also in places far away. However, Kimball et al. (2006) do not include any control variables in their estimation. It is thus hard to judge in how far the decreases in happiness can in fact be attributed to the two disasters.

Second, Berger (2010) uses the 1986 wave of the German Socio-Economic Panel (SOEP) to study the reaction of the panel members to the Chernobyl disaster, which occurred in late April 1986.[12] Since each annual wave of the survey consists of interviews conducted in the period in between March and October, the data can be divided into two groups: respondents which completed the interview before and after the disaster. However, Berger (2010) finds no significant difference in self-reported life satisfaction when controlling for a bunch of socio-demographic control variables. Interestingly enough, the respondents interviewed after the Chernobyl disaster are significantly more concerned with environmental protection. Thus, although the respondents were well aware of the consequences of the disaster, this awareness did not result in a significant reaction of reported life satisfaction.

Third, Yamamura (2012) studies the long-term effects of the large earthquake in Kobe which occurred in 1995. In order to do so, Yamamura (2012) uses data from the Japanese General Social Surveys, which were conducted in Japan in between 2000 and 2008 al-

[12]Different from the nuclear accident in Fukushima, the Chernobyl disaster was not triggered by a natural catastrophe. We nevertheless report the results here, because the effects are perceived quite similar to those of a natural disaster.

most annually. The surveys also include a question on perceived happiness and allow to draw conclusions on whether the respondents lived in the Kobe region when the earthquake unfolded. After controlling for various socio-demographic control variables Yamamura (2012) finds the survivors of the Kobe earthquake to be significantly happier than the respondents from other Japanese regions. The author concludes that surviving a large natural disaster has a long-lasting positive effect on subjective well-being.

We might conclude that the comparatively small literature on the effects of natural disasters on subjective well-being has yet mostly concentrated on studying single disaster events.[13] Moreover, these studies are not primarily concerned with the effects of disaster risk but focus on the short-term well-being-effect of natural disasters.

3 Data and Descriptive Statistics

In order to study the effect of perceived hurricane risk on subjective well-being we collect and combine information from two different data sources. First, we make use of micro-data from the integrated European (EVS) and World Values Survey (WVS). This survey is conducted in a large number of countries around the globe and contains information on both earlier discussed concepts of subjective well-being as well as numerous control variables. Second, in order to approximate (perceived) hurricane risk, we use data from a meteorological database: the Best Track Dataset of hurricanes provided jointly by a number of meteorological research institutes. In the following we describe both databases in more detail.

3.1 Integrated European and World Values Survey

The World Values Surveys build on the European Values Study (EVS), which was first carried out in 1981. While the first wave of the EVS covered 16 countries, primarily located in Europe, the survey was extended to more and more countries around the globe and developed into the World Values Survey in the course of time. Today the network of countries consists of more than 100 countries. At the time when this paper was written, 5 waves of the integrated EVS/WVS survey were available. As the early waves cover only a few and mostly European countries, we use the 3rd, the 4th- and the 5th wave of the integrated EVS/WVS survey, covering the years from 1995 to 2009.[14]

The EVS/WVS surveys have the advantage that they collect, inter alia, data for both concepts of subjective well-being discussed earlier: happiness and life satisfaction.

[13] The only exception is the multicountry panel study by Luechinger and Raschky (2009), covering floods in 15 European countries.

[14] Tables 8 and 9 in the Appendix give an overview on the sample countries and periods.

With respect to happiness, individuals can state when "taking all things together" they are "very happy", "rather happy", "not very happy", or "not at all happy". Concerning life satisfaction, individuals are asked: "All things considered, how satisfied are you with your life as a whole these days?". Answers can be given within a range from 1 ("completely dissatisfied") to 10 ("completely satisfied"). Thus, the variable "happiness" has four categories, while "life satisfaction" has ten.

In order to take the heterogeneity of the respondents adequately into account, we control for numerous individual characteristics in our estimation approach. Among them is the age and the gender of the respondent, the marital status (dummies for married, separated and widowed respondents), the employment status (dummies for unemployed, retired and studying respondents), the education level (dummy for highly educated respondents), individual income (dummies for respondents with low and high income) and the self-reported freedom of choice as a measure of the locus of control (Rotter, 1990). The choice of the control variables is based on the earlier cited empirical literature on the determinants of well-being. All employed control variables were taken from the EVS/WVS database.

3.2 Best Track Data of Hurricanes

Hurricanes are a specific and highly destructive form of storms.[15] They belong to the storm class of cyclones, which are defined as areas of low atmospheric pressure, characterized by rotating winds. As a consequence of the Coriolis effect, cyclones rotate counterclockwise in the Northern and clockwise in the Southern Hemisphere. Depending on their region of origin, cyclones are classified as tropical or extratropical. Tropical cyclones develop between 5 and 20 degrees latitude and thus over warm water. On the contrary, extratropical cyclones have cool central cores as they typically form between 30 and 70 degrees latitude in association with weather fronts. The two types of cyclones can have quite similar destructive effects, however, they differ in their source of energy and their structure. 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 front.

According to the National Oceanic and Atmospheric Administration (NOAA) tropical cyclones with a maximum sustained wind of 38 mph (61 km/h) or less are called "tropical depressions". Whenever a tropical cyclone reaches winds of at least 39 mph (63 km/h) they are typically called "tropical storms". At this stage they 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

[15]The following expositions are primarily based on Keller and DeVecchio (2012).

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”.

Hurricanes (or more general tropical cyclones) are further classified according to their wind speed. This is often done by employing the Saffir Simpson Scale (see Table 1).[16] The Saffir Simpson Hurricane Wind Scale is a 1 to 5 rating based on the hurricane's intensity. This scale only addresses the wind speed and does not take into account the potential for other hurricane-related impacts such as storm surge and rainfall-induced 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 empirical analysis, is based on data from a meteorological database: the Best Track Dataset of tropical cyclones provided jointly by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center (Atlantic and eastern North Pacific hurricanes) and the Oceanography Center / Joint Typhoon Warning Center (Indian Ocean, western North Pacific, and Oceania hurricanes).[17] The advantage of this database is its worldwide coverage. The Best Track dataset provides data on the position of tropical cyclone centers in 6-hourly intervals[18] in its geographic coordinates, the measured maximal sustained wind speed in knots,[19] central surface pressure data in millibar and the Saffir Simpson Hurricane Wind Scale rating of the referring storm interval. The data is collected post-event from different sources like reconnaissance aircraft, ships and weather satellites.

Most of the time, hurricanes are located over the open sea. While tropical cyclones might cause some damage there, e.g. at oil platforms or ships, the referring storm periods are a thread to life and/or wealth for only a minimal fraction of the population. We therefore concentrate on storm periods occurring over land masses. Most of these storm periods are located in coastal areas. This is due to the fact that tropical cyclones

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

[17]The dataset was downloaded from the Unisys Weather Hurricane Data Archive at: http://weather.unisys.com/hurricane/index.php. For our purposes we used the tracking information files for each single hurricane provided in the annual storm tracking data.

[18]The data is recorded on a daily basis at 12am, 6am, 12pm, and 6 pm.

[19]The database contains the average maximum sustained wind speed at 10 metres above the earth's surface over a one minute time span anywhere within the tropical cyclone.

Table 1: Saffir Simpson Hurricane Wind Scale

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.

Source: http://www.nhc.noaa.gov/aboutsshws.php rapidly diminish when a cyclone's eye passes land masses. Atop land masses a storm lacks moisture and heat provided by the ocean. As a consequence it quickly loses power and starts diminishing. However, as the destructive power of a tropical cyclone goes well beyond a cyclone's center we follow Yang's (2005) proposal to include all 6-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. This buffer zone might be justified by the typical structure of tropical cyclones. Its strongest winds are located in the eyewall, a ring of tall thunderstorms located around the cyclone's eye. The eye is the calmest part of the tropical cyclone with a typical diameter of in between 32 and 64 kilometers. Around the eyewall and arranged like a spiral, there are curved rainbands producing heavy rain, wind and tornadoes. The destructive winds and rains of a tropical cyclone affect a wide area. Hurricane winds may extend to more than 242 kilometers from the eye of a large tropical cyclone. Because this extension may vary considerably from case to case, a cautious buffer of 160 kilometers seems to be reasonable.

Using the described Best Track Dataset we construct two different hurricane indicators: The first indicator (F) is the annual sum of all six-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. Note that this indicator is not a pure frequency indicator of hurricanes, as it bases on the number of six-hourly storm periods. Thus, storms which are located over landmasses for longer periods of time have a higher impact on the indicator than quickly decaying hurricanes. Moreover, more severe hurricanes are also more likely to exist for longer periods of time. For reasons of simplicity, we nevertheless refer to this indicator as "frequency indicator" in the following. The second hurricane indicator, we calculate for our empirical analysis, also incorporates storm severity. This indicator, we refer to as "severity indicator" in the following (S), is defined as the annual sum of Saffir-Simpson gradings of all six-hourly storm intervals whose centers pass a country's borders up to a 160 kilometer distance.

3.3 Descriptive Statistics of Combined Dataset

In the following we provide a brief overview on the combined dataset. Tables 2 and 3 report the mean values of the employed control variables for selected countries and the whole country sample.

The average respondent in our sample is 40 years old, 12% of all respondents are retired. Our sample is almost balanced with respect to gender. Most respondents are married (63%), however, we also have numerous separated (5%) and widowed (6%) individuals in our sample. The share of respondents declaring to have at least one child amounts to 71%. By far the most respondents in our sample are actively working. However, 10% declare to be unemployed, 12% are retired and 8% are students. The

Table 2: Variable means part I (selected countries)

Country	Life satisfaction	Happiness	Hurricane frequency (F)	Hurricane severity (S)	Female	Age	Children	Married	Separated	Widowed
Australia	7.47	3.33	18.34	45.57	0.53	45.79	0.70	0.63	0.10	0.07
Brazil	7.64	3.24	0.00	0.00	0.58	39.96	0.72	0.58	0.09	0.06
Canada	7.80	3.41	3.00	3.00	0.59	47.32	0.74	0.57	0.10	0.08
China	6.73	2.96	14.81	24.60	0.51	41.73	0.86	0.85	0.01	0.03
Colombia	8.31	3.33	1.34	1.67	0.49	36.37	0.71	0.60	0.06	0.03
Dominican Rep.	7.13	3.05	5.00	6.00	0.59	28.72	0.47	0.40	0.07	0.01
France	6.86	3.24	0.00	0.00	0.52	47.14	0.72	0.63	0.10	0.08
Germany	6.93	2.97	0.00	0.00	0.55	47.06	0.72	0.64	0.09	0.09
India	5.82	3.01	0.34	0.34	0.44	39.14	0.86	0.80	0.01	0.04
Indonesia	6.93	3.17	0.66	0.66	0.48	38.93	0.69	0.45	0.01	0.06
Japan	6.71	3.17	22.00	46.03	0.55	47.43	0.78	0.74	0.04	0.04
Mexico	7.90	3.24	22.13	40.47	0.50	37.09	0.73	0.60	0.06	0.05
Philippines	6.75	3.29	16.00	25.50	0.50	37.50	0.72	0.71	0.01	0.04
Puerto Rico	8.25	3.39	3.09	6.80	0.65	44.25	0.77	0.56	0.13	0.09
Viet Nam	6.86	3.25	3.60	6.00	0.50	41.47	0.80	0.75	0.01	0.04
Spain	6.97	3.05	0.00	0.00	0.51	45.82	0.67	0.61	0.03	0.08
Great Britain	7.57	3.32	0.00	0.00	0.52	45.74	0.52	0.59	0.09	0.09
United States	7.54	3.34	9.41	14.39	0.52	46.42	0.74	0.58	0.12	0.07
All sample countries	6.44	3.04	1.97	3.63	0.52	40.44	0.71	0.63	0.05	0.06

income dummies for very low and very high incomes exhibit the typical skewness of the income distribution. While 38% declare to belong to one of the lowest three income classes, only 3% do so for the highest two classes. 15% of all respondents are highly educated. On average, individuals in the sample countries report a life satisfaction of 6.44 and a happiness of 3.04 over the entire sample period. Tables 2 and 3 reveal a significant degree of country-variation in the control variables. Thus, a purely descriptive analysis is of little use.

Table 2 also reports on the two earlier described hurricane indicators. The displayed values indicate that hurricanes are comparatively rare events. The countries which are most concerned with hurricanes are Mexico, Japan, Australia, the Philippines, China and the United States. However, numerous additional countries also suffer from hurricane events. Figure 1 shows the distribution of hurricane events for the two earlier described hurricane indicators on an annual basis over the entire sample period. Obviously, both distributions are highly right-skewed. Thus, years with excessive hurricane periods (or severity) are comparatively rare.

4 Estimation Approach

The explanatory variables in our empirical analysis are the two earlier described measures of self-reported well-being. As both left-hand variables, happiness and life satisfaction, only have a few discrete ordered outcomes, the standard linear regression approach, employing the OLS technique, is inapplicable here. Instead we rely on the ordered logit approach for our empirical analysis, as it is usual in the related empirical

Table 3: Variable means part II (selected countries)

Country	Highly educated	Unemployed	Retired	Student	Low income	High income	Freedom of choice
Australia	0.15	0.01	0.24	0.04	0.37	0.09	0.86
Brazil	0.09	0.16	0.13	0.05	0.38	0.01	0.83
Canada	0.18	0.09	0.24	0.04	0.33	0.08	0.87
China	0.05	0.04	0.05	0.02	0.29	0.00	0.77
Colombia	0.17	0.11	0.02	0.07	0.47	0.05	0.88
Dominican Rep.	0.38	0.04	0.01	0.20	0.38	0.06	0.84
France	0.15	0.08	0.24	0.05	0.55	0.02	0.70
Germany	0.19	0.10	0.28	0.06	0.26	0.02	0.74
India	0.18	0.09	0.02	0.24	0.52	0.00	0.72
Indonesia	0.27	0.05	0.04	0.12	0.16	0.01	0.82
Japan	0.24	0.02	0.10	0.03	0.39	0.08	0.69
Mexico	0.12	0.06	0.03	0.08	0.43	0.07	0.87
Philippines	0.17	0.20	0.03	0.07	0.27	0.01	0.72
Puerto Rico	0.30	0.05	0.20	0.06	0.58	0.02	0.90
Viet Nam	0.05	0.05	0.10	0.02	0.11	0.00	0.78
Spain	0.11	0.09	0.19	0.06	0.32	0.01	0.72
Great Britain	0.11	0.06	0.22	0.05	0.21	0.21	0.84
United States	0.19	0.06	0.18	0.02	0.20	0.07	0.87
All sample countries	0.15	0.10	0.12	0.08	0.38	0.03	0.73

literature.[20]

In order to study whether perceived hurricane risk has an influence on happiness and life satisfaction we regress both measures of well-being on (i) a suitable proxy of perceived hurricane risk and (ii) a number of additional control variables on the respondent-level. In order to control for country-specific effects (beyond differences in hurricane risk) we estimate the ordered logit model with country-fixed effects. Moreover, we allow for a common time-trend of the explanatory variable. The model to be estimated is thus given by

$$Prob\left(W_{i,j,t} = k\right) = Prob\left(\lambda_{k-1} < \alpha_j + \beta \cdot X_{i,j,t} + \gamma \cdot R_{j,t} + \delta \cdot t + \epsilon_{i,j,t} \leq \lambda_k\right), \tag{1}$$

where $W_{i,j,t}$ is well-being (happiness or life satisfaction) of individual i, living in country j. The variable t denotes time, $X_{i,j,t}$ is the vector of individual control variables and $R_{j,t}$ is the indicator of perceived hurricane risk in country j. We estimate the model using the maximum likelihood technique. However, in our estimation we have to consider that the measure of hurricane risk $R_{j,t}$ has the same value for all respondents from the same country and the same year. As Chamberlain (1980) and Ferrer-i-Carbonell and Frijters (2004) argue, the inclusion of macro-variables in microeconometric regressions require to estimate the model with a clustered error term. We follow this procedure and estimate the ordered logit model using a robust maximum-likelihood procedure.

A central issue in our estimation approach is to construct a suitable proxy for perceived hurricane risk. It seems to be appropriate to assume that individuals base their assessment of hurricane risk on information on the frequency and/or the severity of hurricanes that occurred in the past. Whenever natural disasters take place, at least

[20] For a detailed description of the ordered logit approach see Greene (2008), chapter 23.

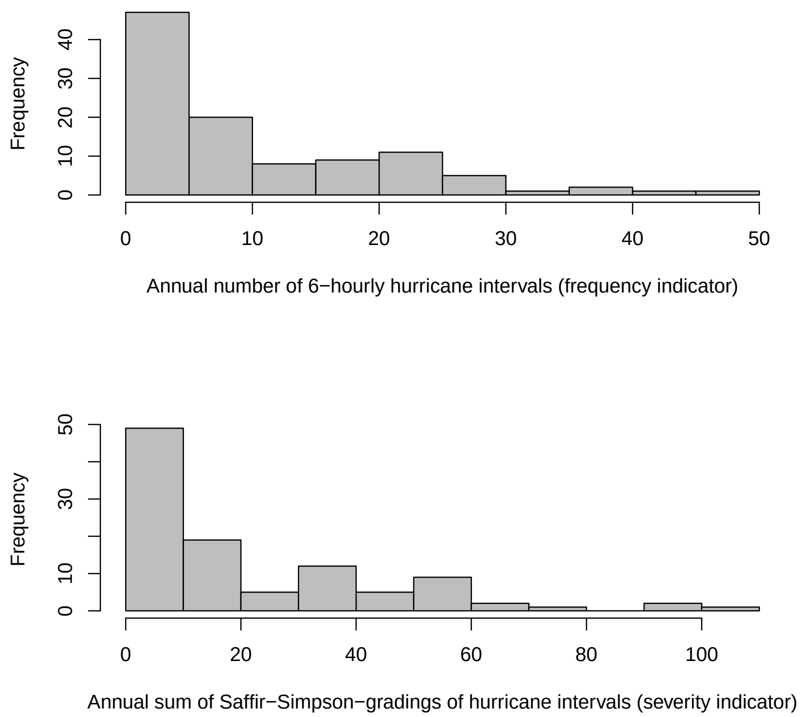

Figure 1: Distribution of hurricane indicators (zero values excluded)

the media in the referring country typically report intensively on the disaster and its severity. One might expect that an increasing number and/or an increasing severity of hurricanes in general will lead to the perception of higher hurricane risk. However, it is less clear over which time-horizon individuals evaluate hurricane risk. It is well conceivable that individuals base their risk assessment only on the very recent past. However, as hurricanes are comparatively rarely occurring events, basing risk assessments on short periods of time leads to highly distorted risk assessments. One might therefore expect that individuals evaluate hurricane risk over longer periods of time, e.g. take at least various years into account when making their assessment. As disaster risk is subject to change in the course of time, e.g. in consequence of changing climate conditions, one might also expect that individuals do not consider the complete past when evaluating hurricane risk. A strictly limited number of considered periods is also likely because most individuals will judge disaster risk in an ad-hoc manner and are somewhat oblivious. In the light of these considerations it seems to be reasonable to expect that individuals base their hurricane risk assessment on the last 5 up to 10 years. However, as we cannot rule out shorter and even longer evaluation periods, we generate a broad range of hurricane risk indicators and study how they perform in our estimation approach.

Within our empirical study we approximate perceived hurricane risk by the n-year-average of the two earlier described hurricane indicators. The hurricane risk measure R^F based on the frequency indicator F is thus defined as

$$R^F_{t,n} = \frac{\sum_{m=1}^{n} F_{t-i}}{n}.$$

Similarly, the hurricane risk measure R^S based on the severity indicator S is given by

$$R^S_{t,n} = \frac{\sum_{m=1}^{n} S_{t-i}}{n}.$$

Following the above expositions, we calculate both hurricane risk indicators for a wide range of evaluation periods ($n \in 1, 2, \ldots, 15$).

For both measures of well-being, we estimate the logit model from equation 1 for both (sets of) risk indicators.

5 Happiness and Hurricane Risk

In a first step, we study whether our indicators of perceived hurricane risk have an effect on happiness as the short-term component of self-reported well-being. Table 4 reports the logit estimation results for the risk measure R^F, derived from the hurricane frequency indicator.[21]

Model 1 reports the results of a baseline regression including all control variables except the hurricane risk indicator. Most of the included control variables turn out to have coefficients significantly different from zero. Moreover, the coefficients coincide with earlier findings in the happiness literature. Female respondents report higher happiness values than their male counterparts. Age has the typical u-shaped effect. Married respondents report higher happiness than singles, while the opposite holds true for separated and widowed respondents. Highly educated individuals are more happy than the rest. Unemployed individuals exhibit lower happiness than their employed counterparts. Retired respondents turn out to be less happy while students are more happy. We also find a significant effect of income on happiness. Individuals with high income are more and respondents with low income are less happy than individuals with medium-sized income. Finally, we find the locus of control to have a significant effect on self-reported happiness. Individuals reporting to have a high level of freedom of choice and control over their life tend to report significantly higher happiness.

The models 2-5 include various versions of the frequency indicator of hurricane risk. The coefficients of the included control variables remain highly stable. With the exception of the five-year average of the frequency indicator, the estimated coefficients

[21] For reasons of clarity, we refrain from reporting the country-fixed effects and the time trend. The complete results are available from the author on request.

turn out to be negative. However, only the indicator based solely on the preceding period turns out to be significantly different from zero on the 90%-confidence level.

Table 5 reports the results for the alternative hurricane risk measure, derived from the hurricane severity indicator. Model 1 reports again the results of the baseline regression without hurricane risk indicator. Model 6 contains the severity indicator which is based solely on the preceding period. The models 7, 8 and 9 employ the five-year, the ten-year and the fifteen-year averaged severity indicator. Again, the hurricane risk measures deliver negative coefficients in three out of four cases. However, none of these coefficients is different from zero on conventional levels of confidence.

For reasons of clarity Tables 4 and 5 report only the results for a few variants of the frequency and the severity indicator. As we do not know exactly how individuals from their expectations on hurricane risk one might be interested in a more systematic evaluation of the two indicators. In order to gain a more systematic picture of the effect of our two hurricane risk indicators on happiness we repeat our estimations for all averaging periods in between one and fifteen. The results of these estimations are summarized in Figure 2. The upper left diagram shows the estimated coefficients of the frequency indicators, the upper right diagram the estimates of the severity indicators. The two diagrams in the lower part of the figure display the p-values of the estimated coefficients.

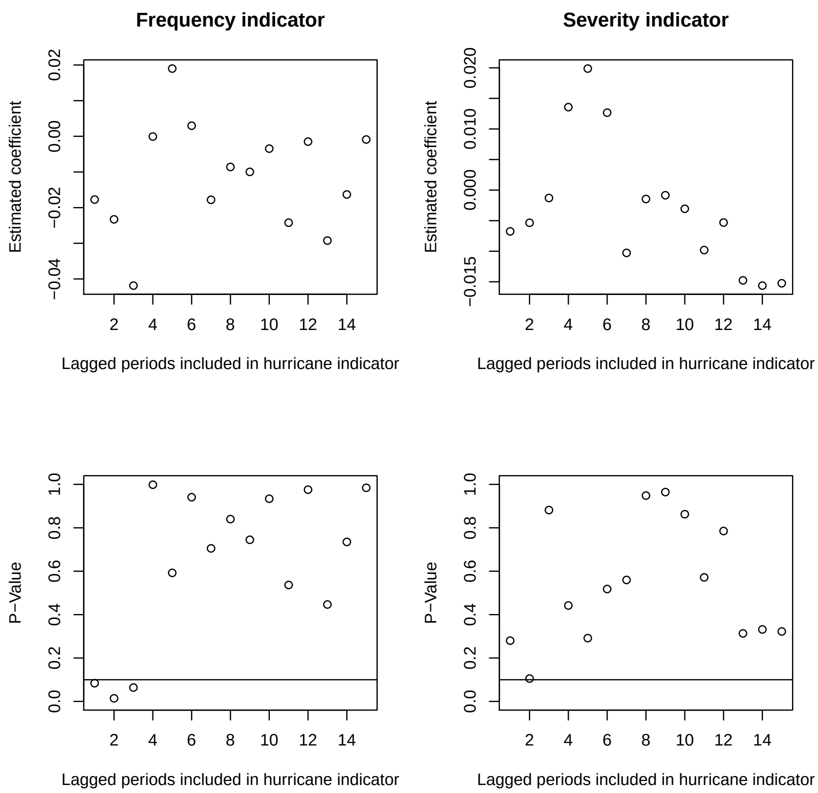

Figure 2: Estimated coefficients hurricane risk and happiness

Table 4: Happiness and hurricane risk (based on frequency indicator)

	Model 1	Model 2 $n = 1$	Model 3 $n = 5$	Model 4 $n = 10$	Model 5 $n = 15$
Control variables					
Female (dummy)	0.1346^{***}	0.1370^{***}	0.1360^{***}	0.1362^{***}	0.1361^{***}
	(0.0195)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Age	-0.0533^{***}	-0.0533^{***}	-0.0535^{***}	-0.0535^{***}	-0.0535^{***}
	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)
Age squared	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	0.0009	0.0007	−0.0019	−0.0002	−0.0003
	(0.0305)	(0.0311)	(0.0314)	(0.0313)	(0.0311)
Married (dummy)	0.4289^{***}	0.4291^{***}	0.4338^{***}	0.4316^{***}	0.4316^{***}
	(0.0354)	(0.0359)	(0.0354)	(0.0358)	(0.0357)
Separated (dummy)	-0.2910^{***}	-0.2899^{***}	-0.2849^{***}	-0.2871^{***}	-0.2869^{***}
	(0.0447)	(0.0451)	(0.0444)	(0.0447)	(0.0447)
Widowed (dummy)	-0.2452^{***}	-0.2467^{***}	-0.2402^{***}	-0.2426^{***}	-0.2425^{***}
	(0.0394)	(0.0397)	(0.0396)	(0.0397)	(0.0396)
Highly educated (dummy)	0.1030^{***}	0.1095^{***}	0.1051^{***}	0.1065^{***}	0.1063^{***}
	(0.0244)	(0.0247)	(0.0249)	(0.0247)	(0.0248)
Unemployed (dummy)	-0.3422^{***}	-0.3395^{***}	-0.3398^{***}	-0.3397^{***}	-0.3397^{***}
	(0.0398)	(0.0400)	(0.0398)	(0.0399)	(0.0398)
Retired (dummy)	-0.0690^{**}	-0.0693^{**}	-0.0678^{**}	-0.0684^{**}	-0.0683^{**}
	(0.0320)	(0.0321)	(0.0321)	(0.0320)	(0.0321)
Student (dummy)	0.0971^{***}	0.0950^{***}	0.0953^{***}	0.0954^{***}	0.0953^{***}
	(0.0267)	(0.0267)	(0.0268)	(0.0271)	(0.0269)
Low income (dummy)	-0.3861^{***}	-0.3833^{***}	-0.3869^{***}	-0.3864^{***}	-0.3865^{***}
	(0.0295)	(0.0300)	(0.0298)	(0.0301)	(0.0300)
High income (dummy)	0.2691^{***}	0.2620^{***}	0.2684^{***}	0.2677^{***}	0.2677^{***}
	(0.0444)	(0.0438)	(0.0445)	(0.0441)	(0.0443)
Freedom of choice (dummy)	0.6442^{***}	0.6399^{***}	0.6403^{***}	0.6402^{***}	0.6402^{***}
	(0.0353)	(0.0353)	(0.0353)	(0.0352)	(0.0352)
Number of hurricane periods...					
...1st lag		-0.0177^{*}			
		(0.0103)			
...5-year avg.			0.0190		
			(0.0355)		
...10-year avg.				−0.0034	
				(0.0416)	
...15-year avg.					−0.0009
					(0.0460)
Num. obs.	133149	131092	131092	131092	131092
Pseudo R^2	0.2168	0.2187	0.2182	0.2181	0.2181
L.R.	28434.3209	28290.2263	28210.0875	28197.8000	28197.6134

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Happiness and hurricane risk (based on severity indicator)

	Model 1	Model 6 $n = 1$	Model 7 $n = 5$	Model 8 $n = 10$	Model 9 $n = 15$
Control variables					
Female (dummy)	0.1346***	0.1367***	0.1361***	0.1362***	0.1364***
	(0.0195)	(0.0196)	(0.0196)	(0.0197)	(0.0197)
Age	−0.0533***	−0.0534***	−0.0535***	−0.0535***	−0.0534***
	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)
Age squared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	0.0009	0.0003	−0.0037	−0.0001	0.0006
	(0.0305)	(0.0310)	(0.0316)	(0.0312)	(0.0312)
Married (dummy)	0.4289***	0.4299***	0.4355***	0.4315***	0.4309***
	(0.0354)	(0.0358)	(0.0353)	(0.0358)	(0.0359)
Separated (dummy)	−0.2910***	−0.2888***	−0.2831***	−0.2873***	−0.2885***
	(0.0447)	(0.0450)	(0.0443)	(0.0448)	(0.0450)
Widowed (dummy)	−0.2452***	−0.2453***	−0.2387***	−0.2428***	−0.2437***
	(0.0394)	(0.0396)	(0.0396)	(0.0397)	(0.0398)
Highly educated (dummy)	0.1030***	0.1083***	0.1040***	0.1068***	0.1076***
	(0.0244)	(0.0247)	(0.0249)	(0.0247)	(0.0247)
Unemployed (dummy)	−0.3422***	−0.3398***	−0.3401***	−0.3396***	−0.3394***
	(0.0398)	(0.0399)	(0.0398)	(0.0399)	(0.0399)
Retired (dummy)	−0.0690**	−0.0690**	−0.0671**	−0.0684**	−0.0690**
	(0.0320)	(0.0321)	(0.0320)	(0.0320)	(0.0321)
Student (dummy)	0.0971***	0.0946***	0.0954***	0.0954***	0.0958***
	(0.0267)	(0.0268)	(0.0268)	(0.0270)	(0.0270)
Low income (dummy)	−0.3861***	−0.3848***	−0.3866***	−0.3863***	−0.3854***
	(0.0295)	(0.0301)	(0.0297)	(0.0300)	(0.0299)
High income (dummy)	0.2691***	0.2651***	0.2671***	0.2680***	0.2681***
	(0.0444)	(0.0443)	(0.0442)	(0.0439)	(0.0443)
Freedom of choice (dummy)	0.6442***	0.6400***	0.6403***	0.6401***	0.6397***
	(0.0353)	(0.0353)	(0.0353)	(0.0352)	(0.0352)
Severity of hurricanes...					
...1st lag		−0.0068			
		(0.0063)			
...5-year avg.			0.0199		
			(0.0189)		
...10-year avg.				−0.0031	
				(0.0177)	
...15-year avg.					−0.0152
					(0.0154)
Num. obs.	133149	131092	131092	131092	131092
Pseudo R^2	0.2168	0.2183	0.2184	0.2181	0.2182
L.R.	28434.3209	28229.3809	28243.7013	28198.4032	28208.7898

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

With the exception of three cases, the frequency indicator delivers negative coefficients. However, only the short-sighted variants (the first lag, the two- and the three-year average) of the frequency indicator deliver a significantly negative coefficient. All indicator variants with longer memory turn out to be insignificant at conventional confidence levels. Thus, happiness tends only to be affected by hurricane risk, when we employ a risk indicator which is based on the very recent past. As explained earlier, these short-sighted risk indicators are comparatively poor measures of factual hurricane risk. However, as happiness is the more volatile and short-sighted component of well-being it seems to be reasonable that individuals report lower happiness values only if hurricanes occurred in the very recent past.[22]

However, an inspection of the results from the estimations using the severity indicator of hurricane risk sows some seeds of doubt on the question, whether happiness is influenced by hurricane risk at all. As the right column of figure 2 indicates, none of the fifteen estimated coefficients turns out to be significantly different from zero.

Altogether we find only weak empirical evidence in favour of the hypothesis that hurricane risk affects self-reported happiness. If at all, happiness is negatively affected by disasters which occurred in the very recent past. More reasonable hurricane risk measures, calculated on the basis of more than the three preceding years, tend to be unrelated to happiness. We therefore conclude that individuals tend to disregard hurricane risk in their assessment of current happiness.

6 Life Satisfaction and Hurricane Risk

In the next step of our analysis we study whether the two described measures of hurricane risk are related to self-reported life satisfaction, the second dimension of individual well-being.

Again, we start out with an analysis of the frequency indicator. The referring estimation results are shown in Table 6. Model 10 is the baseline estimation of the determinants of life satisfaction. We make use of the same set of control variables as in the earlier described happiness regressions. With the exception of the dummy variable for widowed individuals,[23] the baseline model delivers qualitatively the same results as the happiness models. Interestingly enough, the models explaining life satisfaction deliver systematically higher Pseudo R^2 values as the happiness regressions summarized in the previous section. Thus, the more far-sighted and thoughtful component of

[22] Note that we already controlled for numerous factors through which natural disasters might directly affect individual happiness. Thus, the remaining effect can - more or less - be attributed to hurricane risk.

[23] While we found widowed individuals to report significantly lower levels of happiness, we find no such effect for self-reported life satisfaction.

Table 6: Life satisfaction and hurricane risk (based on frequency indicator)

	Model 10	Model 11	Model 12	Model 13	Model 14
		$n = 1$	$n = 5$	$n = 10$	$n = 15$
Control variables					
Female (dummy)	0.1068***	0.1078***	0.1077***	0.1081***	0.1079***
	(0.0156)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Age	−0.0469***	−0.0467***	−0.0468***	−0.0466***	−0.0466***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Age squared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	−0.0187	−0.0210	−0.0197	−0.0179	−0.0194
	(0.0293)	(0.0297)	(0.0296)	(0.0297)	(0.0297)
Married (dummy)	0.2830***	0.2819***	0.2803***	0.2804***	0.2809***
	(0.0344)	(0.0348)	(0.0350)	(0.0354)	(0.0351)
Separated (dummy)	−0.1583***	−0.1598***	−0.1612***	−0.1643***	−0.1622***
	(0.0389)	(0.0395)	(0.0396)	(0.0398)	(0.0398)
Widowed (dummy)	−0.0277	−0.0281	−0.0293	−0.0320	−0.0295
	(0.0398)	(0.0402)	(0.0404)	(0.0406)	(0.0405)
Highly educated (dummy)	0.0919***	0.0889***	0.0896***	0.0948***	0.0906***
	(0.0248)	(0.0250)	(0.0253)	(0.0252)	(0.0251)
Unemployed (dummy)	−0.3385***	−0.3363***	−0.3362***	−0.3349***	−0.3360***
	(0.0376)	(0.0377)	(0.0376)	(0.0378)	(0.0377)
Retired (dummy)	−0.0676**	−0.0688**	−0.0691**	−0.0713**	−0.0699**
	(0.0314)	(0.0316)	(0.0316)	(0.0315)	(0.0316)
Student (dummy)	0.0756**	0.0723**	0.0723**	0.0748**	0.0730**
	(0.0330)	(0.0331)	(0.0329)	(0.0323)	(0.0328)
Low income (dummy)	−0.4675***	−0.4665***	−0.4666***	−0.4639***	−0.4650***
	(0.0391)	(0.0396)	(0.0394)	(0.0392)	(0.0392)
High income (dummy)	0.3306***	0.3275***	0.3281***	0.3319***	0.3294***
	(0.0460)	(0.0462)	(0.0458)	(0.0458)	(0.0456)
Freedom of choice (dummy)	1.1366***	1.1325***	1.1327***	1.1310***	1.1317***
	(0.0490)	(0.0493)	(0.0493)	(0.0493)	(0.0493)
Number of hurricane periods...					
...1st lag		−0.0029			
		(0.0056)			
...5-year avg.			−0.0172		
			(0.0267)		
...10-year avg.				−0.0772***	
				(0.0198)	
...15-year avg.					−0.0624
					(0.0487)
Num. obs.	133718	131656	131656	131656	131656
Pseudo R^2	0.2768	0.2777	0.2777	0.2784	0.2779
L.R.	42675.9655	42184.7329	42194.2171	42312.7873	42229.2227

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

subjective well-being turns out to be more easily predictable than happiness.

Model 11 makes use of the frequency indicator, based on the preceding period. Models 12, 13 and 14 approximate hurricane risk by the 5-, the 10- and the 15-year frequency average. Again the set of control variables remains almost unaffected by the inclusion of the risk measure. The estimated coefficients of the risk measure turn out be negative in all estimations. While the 1-, the 5- and the 15-year average turn out to be insignificant, the 10-year average is significant on the 99%-confidence-level.

When repeating the estimations for the severity indicator (see figure 7), the results are similar. Again, all estimated coefficients are negative. The 10-year average of the severity indicator is significant on the 99%-confidence-level. Moreover, the 15-year average of the severity indicator is now also significant, although only on the 90%-confidence-level.

Again we study the two hurricane risk indicators more systematically by repeating the estimations for all averaging periods in between one and fifteen. The results of these estimations are summarized in Figure 3. Interestingly enough, we find a systematic relation between life satisfaction and hurricane risk for both indicators for averaging periods exceeding six years. When using more than six years, the severity indicator always delivers significantly negative coefficients. A similar pattern exists for the frequency indicator, however, for averaging periods above 14 the indicator gets insignificant again. Moreover, when using more than six averaging periods, the estimated coefficients of the hurricane risk indicator increase in absolute size. Altogether, we thus find robust empirical evidence in favour of the hypothesis that perceived hurricane risk has a significantly negative effect on life satisfaction.

Table 7: Life satisfaction and hurricane risk (based on severity indicator)

	Model 10	Model 15 $n = 1$	Model 16 $n = 5$	Model 17 $n = 10$	Model 18 $n = 15$
Control variables					
Female (dummy)	0.1068***	0.1077***	0.1076***	0.1083***	0.1080***
	(0.0156)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Age	−0.0469***	−0.0468***	−0.0468***	−0.0465***	−0.0465***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Age aquared	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children (dummy)	−0.0187	−0.0211	−0.0196	−0.0179	−0.0182
	(0.0293)	(0.0297)	(0.0297)	(0.0298)	(0.0298)
Married (dummy)	0.2830***	0.2821***	0.2805***	0.2806***	0.2804***
	(0.0344)	(0.0347)	(0.0350)	(0.0354)	(0.0353)
Separated (dummy)	−0.1583***	−0.1596***	−0.1612***	−0.1643***	−0.1636***
	(0.0389)	(0.0395)	(0.0397)	(0.0398)	(0.0399)
Widowed (dummy)	−0.0277	−0.0278	−0.0291	−0.0321	−0.0304
	(0.0398)	(0.0402)	(0.0404)	(0.0405)	(0.0406)
Highly educated (dummy)	0.0919***	0.0886***	0.0896***	0.0950***	0.0924***
	(0.0248)	(0.0250)	(0.0253)	(0.0251)	(0.0251)
Unemployed (dummy)	−0.3385***	−0.3364***	−0.3361***	−0.3349***	−0.3354***
	(0.0376)	(0.0376)	(0.0376)	(0.0378)	(0.0378)
Retired (dummy)	−0.0676**	−0.0687**	−0.0692**	−0.0711**	−0.0708**
	(0.0314)	(0.0316)	(0.0316)	(0.0316)	(0.0316)
Student (dummy)	0.0756**	0.0722**	0.0723**	0.0742**	0.0739**
	(0.0330)	(0.0330)	(0.0330)	(0.0325)	(0.0325)
Low income (dummy)	−0.4675***	−0.4668***	−0.4669***	−0.4643***	−0.4638***
	(0.0391)	(0.0396)	(0.0395)	(0.0391)	(0.0391)
High income (dummy)	0.3306***	0.3281***	0.3291***	0.3334***	0.3303***
	(0.0460)	(0.0460)	(0.0457)	(0.0458)	(0.0456)
Freedom of choice (dummy)	1.1366***	1.1326***	1.1328***	1.1311***	1.1312***
	(0.0490)	(0.0493)	(0.0493)	(0.0493)	(0.0493)
Severity of hurricanes...					
...1st lag		−0.0009			
		(0.0040)			
...5-year avg.			−0.0095		
			(0.0161)		
...10-year avg.				−0.0358***	
				(0.0072)	
...15-year avg.					−0.0394*
					(0.0210)
Num. obs.	133718	131656	131656	131656	131656
Pseudo R^2	0.2768	0.2777	0.2777	0.2785	0.2782
L.R.	42675.9655	42182.2214	42194.8294	42328.2826	42280.4157

Dependent variable: life satisfaction
Ordered logit estimation (clustered standard errors)
Time trend and country-fixed effects not reported
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

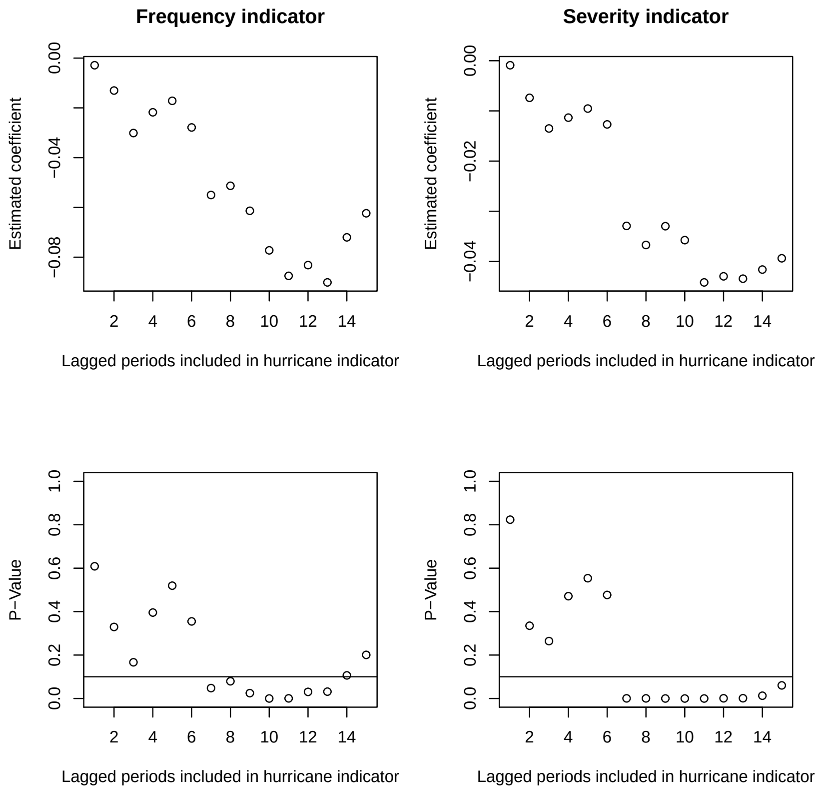

Figure 3: Estimated coefficients hurricane severity and life satisfaction

7 Conclusions

Throughout the last 20 years a growing number of scientists have expressed their worries about global warming. As global warming will likely affect the frequency and/or the severity of certain types of natural disasters, understanding the consequences of climate-induced disasters is urgently necessary. While most of the existing literature has yet primarily focused on the direct effects of natural disasters on economic growth, little attention has yet been devoted to the effect of natural disasters on individual well-being.

In this paper we focused on the effects of hurricane risk on the two most important measures of self-reported well-being, happiness and life satisfaction. The empirical evidence presented in this paper points into the direction that hurricane risk has little effect on perceived individual happiness, at least when controlling for the direct channels through which natural disasters might affect individual well-being. Thus, when evaluating the actual quality of their lives, individuals tend to disregard the risks of being affected by upcoming natural disasters. However, this holds not true when assessing their lives as a whole. We find robust empirical evidence in favour of the hypothesis that when making this more cognitive assessment, individuals tend to take hurricane risk into account and report lower degrees of life satisfaction when hurricane risk is high. We conclude that the effects of natural disasters thus go well beyond the direct growth effects. Whenever the process of global warming increases natural disaster risk, this risk itself is an additional burden for the population, exposed to this risk.

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Appendix

Table 8: Country sample (part I)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Albania	0	0	0	999	0	0	0	1000	0	0	0	0
Algeria	0	0	0	0	0	0	0	1282	0	0	0	0
Andorra	0	0	0	0	0	0	0	0	0	0	1003	0
Argentina	1079	0	0	0	1280	0	0	0	0	0	0	1002
Armenia	0	0	2000	0	0	0	0	0	0	0	0	0
Australia	2048	0	0	0	0	0	0	0	0	0	1421	0
Azerbaijan	0	0	2002	0	0	0	0	0	0	0	0	0
Bangladesh	0	1525	0	0	0	0	0	1500	0	0	0	0
Belarus	0	2092	0	0	0	0	0	0	0	0	0	0
Bosnia	0	0	0	800	0	0	1200	0	0	0	0	0
Brazil	0	0	0	0	0	0	0	0	0	0	0	1500
Bulgaria	0	0	1072	0	0	0	0	0	0	0	1001	0
Canada	0	0	0	0	0	1931	0	0	0	0	0	2164
Chile	0	1000	0	0	0	1200	0	0	0	0	0	1000
China	1500	0	0	0	0	0	1000	0	0	0	0	0
Colombia	0	0	3029	2996	0	0	0	0	0	0	3025	0
Croatia	0	1196	0	0	0	0	0	0	0	0	0	0
Cyprus	0	0	0	0	0	0	0	0	0	0	0	1050
Dominican Rep.	0	417	0	0	0	0	0	0	0	0	0	0
Egypt	0	0	0	0	0	0	3000	0	0	0	0	0
El Salvador	0	0	0	0	1254	0	0	0	0	0	0	0
Estonia	0	1021	0	0	0	0	0	0	0	0	0	0
Finland	0	987	0	0	0	0	0	0	0	0	1014	0
France	0	0	0	0	0	0	0	0	0	0	0	1001
Georgia	0	2008	0	0	0	0	0	0	0	0	0	0
Germany	0	0	2026	0	0	0	0	0	0	0	0	2064
Great Britain	0	0	0	1093	0	0	0	0	0	0	1041	0
Guatemala	0	0	0	0	0	0	0	0	0	1000	0	0
Hong Kong	0	0	0	0	0	0	0	0	0	0	1252	0
Hungary	0	0	0	650	0	0	0	0	0	0	0	0
India	2040	0	0	0	0	0	2002	0	0	0	0	2001
Indonesia	0	0	0	0	0	0	1000	0	0	0	0	2015
Iran	0	0	0	0	0	2532	0	0	0	0	0	0
Iraq	0	0	0	0	0	0	0	0	0	2325	0	2701
Israel	0	0	0	0	0	0	1199	0	0	0	0	0
Italy	0	0	0	0	0	0	0	0	0	0	1012	0
Japan	0	0	0	0	0	1362	0	0	0	0	1096	0
Jordan	0	0	0	0	0	0	1223	0	0	0	0	0
Kyrgyzstan	0	0	0	0	0	0	0	0	1043	0	0	0
Latvia	0	1200	0	0	0	0	0	0	0	0	0	0
Lithuania	0	0	1009	0	0	0	0	0	0	0	0	0
Macedonia	0	0	0	995	0	0	1055	0	0	0	0	0
Malaysia	0	0	0	0	0	0	0	0	0	0	0	1201
Mexico	854	1510	0	0	0	1535	0	0	0	0	1560	0
Moldova	0	984	0	0	0	0	0	1008	0	0	0	1046
Montenegro	0	240	0	0	0	0	1060	0	0	0	0	0
Morocco	0	0	0	0	0	0	1251	0	0	0	0	0

Table 9: Country sample (part II)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Netherlands	0	0	0	0	0	0	0	0	0	0	0	1050
New Zealand	0	0	0	1201	0	0	0	0	0	954	0	0
Nigeria	1996	0	0	0	0	2022	0	0	0	0	0	0
Norway	0	1127	0	0	0	0	0	0	0	0	0	0
Pakistan	0	0	733	0	0	0	2000	0	0	0	0	0
Peru	0	1211	0	0	0	0	1501	0	0	0	0	1500
Philippines	0	1200	0	0	0	0	1200	0	0	0	0	0
Poland	0	0	1153	0	0	0	0	0	0	0	1000	0
Puerto Rico	1164	0	0	0	0	0	720	0	0	0	0	0
Romania	0	0	0	1239	0	0	0	0	0	0	1776	0
Russia	2040	0	0	0	0	0	0	0	0	0	0	2033
Saudi Arabia	0	0	0	0	0	0	0	0	1502	0	0	0
Serbia	0	1280	0	0	0	0	1200	0	0	0	0	0
Serbia and Montenegro	0	0	0	0	0	0	0	0	0	0	1220	0
Singapore	0	0	0	0	0	0	0	1512	0	0	0	0
Slovakia	0	0	0	1095	0	0	0	0	0	0	0	0
Slovenia	1007	0	0	0	0	0	0	0	0	0	1037	0
South Africa	0	2935	0	0	0	0	3000	0	0	0	0	2988
South Korea	0	1249	0	0	0	0	1200	0	0	0	1200	0
Spain	1211	0	0	0	0	1209	0	0	0	0	0	0
Sweden	0	1009	0	0	1015	0	0	0	0	0	0	1003
Switzerland	0	1212	0	0	0	0	0	0	0	0	0	0
Taiwan	0	0	0	0	0	0	0	0	0	0	0	1227
Tanzania	0	0	0	0	0	0	1171	0	0	0	0	0
Trinidad and Tobago	0	0	0	0	0	0	0	0	0	0	0	1002
Turkey	0	1907	0	0	0	0	3401	0	0	0	0	0
Uganda	0	0	0	0	0	0	1002	0	0	0	0	0
Ukraine	0	2811	0	0	0	0	0	0	0	0	0	1000
United States	1542	0	0	0	1200	0	0	0	0	0	0	1249
Uruguay	0	1000	0	0	0	0	0	0	0	0	0	1000
Venezuela	0	1200	0	0	0	1200	0	0	0	0	0	0
Viet Nam	0	0	0	0	0	0	1000	0	0	0	0	1495
Zimbabwe	0	0	0	0	0	0	1002	0	0	0	0	0