THREE ESSAYS ON THE WELFARE IMPACT OF NATURAL AMENITIES AND NATURAL DISASTERS

by

MONA AHMADIANI

(Under the Direction of Susana Ferreira and Craig E. Landry)

ABSTRACT

This dissertation analyzes and investigates the welfare impacts of natural amenities and natural disasters. In the first essay, we shed light on an unresolved puzzle in models of interurban spatial equilibrium; in theory, housing prices and wages should compensate for differences in utility across space. Yet, empirical studies show a large spatial variation in subjective well-being (SWB) across United States counties. We find that these amenities explain a sizable fraction of the variation in county-level life satisfaction and that housing and labor markets do not fully capitalize the environmental and climate-driven spatial variation in the county-average SWB. This is important because the impacts of environmental quality on well-being provide a major rationale for environmental management and regulation.

Finding that climate amenities are particularly important among local environmental conditions, in the second essay, we specifically focus on the impact of billion-dollars natural disasters on SWB and investigate the temporal impact of natural disasters. By utilizing a quasi-experimental design and combining subjective well-being and extreme weather events data, we estimate and monetize the adverse impact of natural disasters and explicitly focus on the intangible direct and indirect costs of natural disasters which are inevitably understated in prior analyses. Our findings illustrate that the impact of events on individual SWB decays six months after the event. This study provides useful information for policy-making, by suggesting a policy-relevant time frame to escalate the community healing process. We then investigate the attenuating impact of health care access, natural-peril insurance, and governmental assistance programs and find a partial compensating role for both private and public protective measures.

The third essay estimates the economic value of multi-peril hazard insurance combining stated and revealed preference data. Our results indicate that the value of multi-peril hazard insurance is substantially higher for households who live in the coastal zone and on the oceanfront and lower for those not required to buy the flood insurance. We find a significant change in the welfare effect of climate-related disaster depending on individual food and erosion risk perceptions. This has clear policy implications as Congress debates on how to restructure the National Flood Insurance Program to enforce risk-rated insurance premium and deal with the financial deficit of NFIP.

INDEX WORDS: Community Resilience, Climate Change, Experienced Utility, Government Assistance Programs, Local Amenities, Mental Health, Multi-Peril Insurance, Natural Disasters, Risk Perception, Spatial Equilibrium, Stated and Revealed Preference Data, Subjective Well-Being, Willingness To Pay

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To

my loving parents

Fatemeh and Rasoul

&

my best friend and husband

Pourya

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CHAPTER 1

INTODUCTION

Economists use various methods (e.g., market-based and nonmarket-based valuation techniques) to determine and quantify the negative and positive, direct and indirect impacts of natural amenities and natural disasters on human well-being; but the understanding of influential roles on the environment is still far from complete. In a collaborative effort, scholarly studies investigate the impacts of environmental amenities to explain their associated welfare gain or loss, and public policy promotes human well-being and improve quality of life through investigation of their impacts on macroeconomic indicators. In recent years, economists have increasingly used subjective well-being (SWB) data, which is an indicator of society's standard of living, to measure experienced utility and to study the impact of public goods and bads on individual's welfare (Welsch, 2002 and 2006, Di Tella and MacCulloch 2008, Rehdanz and Maddison 2009, Luechinger 2009, Levinson 2012, Winter and Li 2016). SWB data can be utilized to monitor progress, to inform policy design, and to support policy evaluation and cost-benefit analysis, particularly where non-market outcomes as in environmental valuation are involved (OECD 2013). However, SWB indicators remain controversial and not fully understood. In this context, it is essential to improve our understanding of SWB as a macroeconomic indicator and to shed lights on unsolved puzzles in this area of study.

A puzzle that has received less attention in the association between SWB and environment concerns the existence of large spatial variations in SWB across, but also within countries. This contradicts the economic theory prediction that in a spatial equilibrium, differences in utility across locations should be eliminated by labor and housing market price differentials.

In the second chapter of this dissertation, "Environmental Amenities and Quality of Life across the United States," we shed light on this puzzle and explore the impact of environmental amenities in explaining the spatial variation in SWB across the U.S. We hypothesize that differences in environmental amenities play a major role in explaining the spatial variation in SWB observed across the U.S. We combine individual-level life satisfaction scores from the Behavioral Risk Factor Surveillance System (BRFSS) by the Centers for Disease Control and Prevention from 2005 to 2010, with county and state-level predictors of SWB, and investigate the degree of association of different factors (climate, geography and environmental externalities, local public goods, access to cultural and urban amenities, and transportation infrastructure) with SWB. We use the answers to a life satisfaction question as our global measure of SWB and utilize a two-step regression approach, that is equivalent to multi-level regression analyses, and investigate the sources of county-level heterogeneity in SWB in the U.S. We find that environmental and climate amenities explain a sizable fraction of the variation in county-level life satisfaction and that housing and labor markets do not fully capitalize the environmental and climate-driven spatial variation in the county-average SWB. This is important because the impacts of environmental quality on well-being provide a major rationale for environmental regulation. We identify the underlying environmental conditions that support high satisfaction with life and rank U.S. counties based on these factors to inform policy on the importance of environmental management. We explain that the remaining variation in regional life satisfaction might be 1) the hedonic "Treadmill Effect" that reduces the utility benefit of environmental and local amenities in the long-term or 2) an evidence that life satisfaction is a term in utility function that utility maximizer agents tend to trade it for other goods and services.

In the third chapter, entitled "Well-being Effects of Extreme Weather Events in the United States," we examine the impact of weather-related disasters on the well-being of U.S. residents from 2004 to 2010 and answer several questions about the way in which weather-related disasters affect individual SWB. The increase in weather and climate disasters in recent years has prompted an interest in analyzing their consequences and required mitigation and adaptation measures to minimize their potentially large impacts on welfare. Based on the 2012 report by Intergovernmental Panel on Climate Change (IPCC), climate change could be altering the frequency, intensity, spatial extent, duration of climate-related extreme weather events. The theoretical measure of economic impacts of natural disasters that would be the change in the welfare due to the event is usually hard to measure. Some impacts, such as the financial losses associated with property damages and the fiscal consequences of reconstruction, are tangible and can be easily quantified. However, natural disasters can also cause stress and other psychological costs (uncertainty, grief for the bereaved, individual and collective traumas) that can be considered as direct impacts to health (injury) or indirect impacts which occur as a result of the initial damage to structure, content, and infrastructure. These intangible costs are very important but are unaccounted for in official economic estimates of disaster damages. The difficulty in estimating the welfare impact of disasters in practice compared to the theoretical straightforward accounting methods of adding direct and indirect costs of natural disasters leads to use of the method of SWB to estimate the economic cost of disasters. The use of SWB is particularly appropriate for estimating the impacts of extreme weather events on human well-being, as this approach accounts for the less tangible costs of natural disasters that are inevitably understated in prior studies. The global measure of life satisfaction combines a cognitive assessment of overall quality of life with an affective, temporary component and both elements can capture the negative impact of disasters depending on the type of effects (i.e. direct and indirect effects). We combine individual survey data from BRFSS, with the storm events and the billion-dollar disaster databases of the National Center for Environmental Information and use a quasi-experimental design that identifies the average impact of six types of billion-dollar disasters (tropical cyclone, severe storm, flooding, drought, freeze, and wildfire) on individual life satisfaction. In addition to estimating the associated welfare loss of extreme weather events, we investigate the impact of the intensity and frequency of disasters and examine the temporal decay in these impacts. We find that the impact of events on individual SWB decays six months after the event. While the community might not bounce back immediately in the aftermath of the disaster, as the support systems are needed for the traumatized individuals in the long-run phase, this study provides useful information for policy-making, by suggesting a policy-relevant time and space frame to escalate the community healing process. Acknowledging that the SWB measures reflects the total net impact of natural disasters on well-being on an affected community, we disentangle the dampening impact of private and public risk transfer and risk reduction measures by including indicators of health insurance, flood insurance, Community Rating System participations, and different types of governmental assistance programs in our analyses and show that individual and community level measures both improve resilience in the face of disasters, especially within first 4 months after the disasters.

In the fourth chapter, "Economic Value of Multi-Peril Coastal Hazard Insurance," we pay particular attention to the use of insurance as an essential component of household and community resilience to mitigate the welfare impacts of natural disasters and reduce future losses from floods. Multi-peril hazard insurance is a useful mitigation measure since natural disasters typically contain a series of extreme weather events and it is complicated for both the insurer and the insured to split the total damages. The issue of financial insolvency of NFIP since its inception and the staggering debt of NFIP due to annual natural disasters is routed from the rating structure and low penetration rate of the insurance market. In this study, we revisit the proposal of multi-peril insurance (Multiple Peril Insurance Act in the U.S. Congress, 2009) and provide evidence on the welfare gain for residents of hazard-prone areas. Specifically, we estimate the economic value of a flood and erosion bundled insurance product as a mitigation measure for residents of coastal areas. Currently, the National Flood Insurance Program (NFIP) offers indemnification from flood hazard in communities that agree to regulate development in the floodplain, but the mapping and regulatory standards of the NFIP do not address erosion risk in coastal areas. Since flooding and erosion risks are highly correlated in coastal areas, we examine households' welfare gain from multi-peril hazard insurance coverage by coupling information on NFIP Policies-in-Force (revealed preference data) with survey data (stated preference data) for a sample of coastal households in the U.S. Southeast. Results indicate that the value of multi-peril hazard insurance is substantially higher for households who live on the oceanfront and lower for those not required to buy the flood insurance. We also find that higher risk perception leads to higher probability of purchasing multi-peril insurance coverage. In this regard, by coupling natural hazard insurances, property owners perceive the risk to be sufficiently high and manage to overcome the systematic bias that arises when making a decision about a low-probability high-consequence event.

CHAPTER 2

ENVIRONMENTAL AMENITIES AND QUALITY OF LIFE ACROSS THE UNITED STATES

2.1 Introduction

Local amenities are a key determinant of where people choose to live and of the geographic distribution of social and economic activity. Interurban hedonic spatial models use the spatial variation in housing prices and wages to infer the value of nonmarket local amenities such as climate and environmental quality. The idea (dating back to Rosen 1979 and Roback 1982, 1988) is that different locations offer different bundles of local amenities and individuals must be compensated (through lower housing prices, higher real wages, or both) to live in objectively unpleasant areas. That is, housing and labor price differentials eliminate the utility advantages of different locations. Otherwise, some individuals would have an incentive to move to more amenable areas where they could gain a higher level of utility.

Following this intuition, "objective" quality of life rakings for different areas can be constructed based on how much households pay in cost-of-living relative to the incomes they receive; that is, by weighing local amenities with their implicit prices, derived from compensating differentials in housing and labor markets (Roback 1988 and 1982, Rosen 1979, Blomquist et al. 1988, Albouy 2008, Bieri et al. 2012).

An alternative, complementary approach studies the relationship between locations and quality of life using self-reported, subjective well-being (SWB) data. Individuals in different locations are asked to answer questions such as "Overall, how satisfied are you with life nowadays on a scale from 1 to 10?" Their answers can be used to measure and compare quality of life across locations (Maddison and Rehdanz 2007, Moro et al. 2008, Oswald and Wu 2010, 2011, Glaeser et al. 2014). In contrast to the hedonic approach that uses objective data on real wages and real housing expenditures to indirectly rank quality of life across locations, SWB data provide direct, self-reported evaluations of quality of life.

A common finding in all the studies that have analyzed the "geography of happiness" is that self-reported SWB varies widely across space. This is the case for international comparisons but also for regional comparison of SWB within the same country.[1] In all the cases, the null hypothesis of equality of well-being across areas is rejected, casting doubt on the existence of an interurban spatial equilibrium of strict equality of utility (Oswald and Wu 2011, Glaeser et al. 2014, Goetzke and Islam 2016). While the set of assumptions in spatial equilibrium models (rationality, perfect information, instantaneous price adjustments, no obstacles to the free mobility of individuals across different areas) is restrictive and unlikely to hold in the real world, one alternative explanation is that revealed preference methods such as hedonic pricing are related to decision utility, which is inferred from observed choices, while SWB data more closely match experienced utility, which entails retrospective evaluations of outcomes (Kahneman et al. 1997).[2] Another explanation is that individuals may care about experienced utility, but also about other objectives. Under this view, SWB might be conceived as an argument (among others) of the utility function (Glaeser et al. 2014).

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[1] Germany in Maddison and Rehdanz (2007), Ireland in Moro et al. (2008), the United States in Oswald and Wu (2010 and 2011), Glaeser et al. (2014), and Goetzke and Islam (2016). Aslam and Corrado (2011) illustrate the importance of regional effects when studying the determinants of individual wellbeing across European countries.

[2] Specifically, deviations between decision and experienced utility can arise from failures in affective forecasting, that is, in predicting the utility consequences of one's choices (Loewenstein and Adler 1995, Loewenstein and Schkade 1999, Loewenstein et al. 2003, Wilson and Gilbert 2003).

Whatever the case may be, the findings of large regional variations in SWB are puzzling and demand an explanation. In this study we investigate the spatial distribution of well-being across the U.S. between 2005 and 2010, and ask not only whether well-being varies across U.S. counties and states but why. We hypothesize that differences in local amenities play an important role, and estimate the relative contribution to SWB of a range of local amenities including climate, geography, environmental externalities, and other local public goods.

The U.S. is a particularly appropriate setting for analyzing the effect of local amenities on life satisfaction due to the diversity in landscapes and environmental conditions which allows the researcher to identify preferences over a broad range of amenities in the cross section (Albouy et al. 2016). On the other hand, compared to many other developed countries, the U.S. exhibits a higher internal geographical mobility (Molloy et al. 2011), and its inhabitants share a cultural context and values that mitigate cross-cultural response bias present in international comparisons of self-reported measures of well-being (Chen et al. 1995, Diener 2000, Eid and Diener 2001, Diener and Diener 2009).

SWB data are becoming widely employed by economists to empirically examine fundamental assumptions and propositions regarding individual's utility (Frey and Stutzer 2002, Di Tella and MacCulloch 2006). Independently of whether they are viewed as a proxy for utility (Blanchflower and Oswald 2004, Clark et al. 2008, Oswald and Wu 2011) or as one of many arguments of the utility function (Glaeser et al. 2014), self-reported SWB indicators can provide key information about people's quality of life and consequently open up a wide range of opportunities to inform theory and policy design.[3]

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[3] The OECD under its Better Life Initiative promotes the use of SWB in addition to other conventional social and economic indicators (e.g. GDP) for monitoring and benchmarking countries' performance, and for designing and

Using data from the BRFSS, Oswald and Wu (2010 and 2011) find statistically significant state-level differences in life satisfaction in the U.S. Using a different dataset, the General Social Survey, Goetzke and Islam (2016) also find evidence of spatial disequilibrium across the nine U.S. census regions. However, both studies stop short of investigating what factors explain regional differences in SWB. In addition to the state, the BRFSS records the county of residence of the respondents. We can thus match individuals to a wide range of local amenities at the county level, which enables us to explore one possible reason behind the variation in SWB across the US geography: differences in county-level environmental endowments and amenities.

Before us, Lawless and Lucas (2011) use county averages to examine correlations between SWB and socioeconomic conditions in the U.S., but they do not consider natural amenities nor control for individual characteristics. Other papers have estimated the direct impact of environmental factors on individual SWB (see e.g. Brereton et al. 2008, Levinson 2012, Winters and Li 2016). Using BRFSS data (the metropolitan specification), Glaeser et al. (2014) study the relationship between declining cities and unhappiness.

The goal of our study is different. We want to explain regional differences in well-being. To do that, we first extract the spatial variation in SWB across U.S. counties conditional on individual socio-demographic characteristics and show that, consistent with previous findings, adjusted life satisfaction differs across counties even when we allow rents and wages to vary to compensate for differences in amenities. We then show that local amenities do explain a non-trivial fraction of the variation in SWB both across and within U.S. counties and compare the relative importance of

delivering policies, as SWB measures can alert policymakers to issues that traditional indicators fail to identify (OECD, 2013). Eurostat, as legislated by the Commission Regulation (EU) No 62/2012 of 24 January 2012, started publishing personal well-being indicators of European countries in 2015. The UK's Office of National Statistics measures and tracks reported personal well-being in different areas of the UK since 2012.

amenity types in explaining regional differences in SWB. We show that for multiple amenities their estimated total and partial effects (conditional on individual income, housing values and county median income) on life satisfaction are similar and different from zero, reinforcing the intuition that labor and housing markets are not fully capitalizing their impacts on life satisfaction.

2.2 Methods

We use the answers to a life satisfaction question as our global measure of SWB and utilize a two-step regression approach to investigate the sources of county-level heterogeneity in SWB in the U.S. [4]

First step regression

We first estimate a life satisfaction regression equation similar to those estimated in the "economics of happiness" literature. Conceptually, SWB scores have been considered an observed variable for a latent level of utility (Blanchflower and Oswald 2004, Clark et al. 2008). In this view, LS_i, the life satisfaction score of individual *i*, is a function of the person's unobserved true well-being or utility plus an error term that includes, among other factors, the measurement error associated with accurately communicating one's true well-being, that is: $\mathrm{LS}_i = \mathrm{f}(U_i) + \varepsilon_i$. In empirical applications, assuming a linear continuous function for f(.), global LS scores are typically expressed as

$$\mathrm{LS}_{ijt} = \alpha + X_{ijt}\beta + \gamma_t + \delta_j + \varepsilon_{ijt}\ , \qquad (1)$$

[4] Evidence from both psychologists and economists shows that self-reported measures of SWB and, in particular, life satisfaction are valid and reliable: they contain 'valid variability' in the sense that they are a strong predictor of future behavior; they correlate with biological measures of positive and negative states (e.g. prefrontal cerebral brain asymmetry, hormone levels such as cortisol), and with reports of family, friends and strangers asked to rate the happiness of the respondent; people who report to be happier smile more); SWB measures are stable, reaching high test–retest reliability scores (Krueger and Schkade 2008, Diener and Tov 2012).

where X_{ij} denotes a matrix of socio-demographic characteristics of individual i at location j, and ε_{ij} is an error term. Equation (1) includes time fixed effects γ_t, and region fixed effects δ_j. (Ideally, α would be individual-specific to control for individual unobserved heterogeneity, but the BRFSS is a repeated cross section, not a panel, so this is not possible in our case.)

If life satisfaction were equalized across locations, then $\delta_r = \delta_l$ for any two locations $r \neq l$, suggesting a straightforward test of spatial variation of life satisfaction (conditional on individual characteristics). We performed an F-test of joint significance of county dummies, a pairwise comparisons of county dummies, and a Kruskal-Wallis test (a non parametric alternative to the one-way ANOVA), to test the null hyphothesis of equal SWB across U.S. counties.[5]

In interurban hedonic models, differences in wages and rents eliminate differences in utility across space. In practice, the violation of any of the underlying assumptions of the model can prevent the spatial equilibrium from being reached. In order to let wages and rents vary to compensate for differences in amenities across locations, the set of individual characteristics X_{ij} in equation (1) does not include those two variables. We acknowledge, however, that our test is, strictly, a test of equality of life satisfaction across locations. To interpret it, more broadly as a test of the equilibrium condition in interurban hedonic models would require, additionally, that life satisfaction scores are a good proxy for decision utility.

Second step regression

The estimation of equation (1) generates a set of county dummy estimates $(\widehat{\delta_j})$, which, as described above, can be used to test the equality of LS across counties. These county dummies represent

[5] We also performed unconditional tests in which the county dummies were estimated in regressions that did not include individual controls.

regression-adjusted measures of well-being in a county—the level not explained by individual personal characteristics. They capture, for example, regional characteristics affecting the life satisfaction of their residents.

In the second step regression we analyze the relative contribution of a vector of time-variant and time-invariant regional characteristics (Z_{jt}) representing climate, geography, environmental externalities, local public goods, access to cultural and urban amenities, and transportation infrastructure, to explain the residual county-level life satisfaction. That is, we estimate

$$\widehat{\delta_{Jt}} = \varphi + Z_{jt}\theta + \gamma_t + v_{jt} \tag{2}$$

where $\widehat{\delta_{Jt}}$ are county fixed effects for each of the six years in our study (2005-2010).[6]

In the baseline specification of equations (1) and (2) we do not control for variables that in hedonic models compensate for amenity differences across locations. That is, in equation (1) the set of individual regressors X_{ijt} does not include income, and in equation (2) we do not control for county-level housing values and wages. However, we also estimate alternative specifications of equations (1) and (2) in which we do control for them.[7] The inclusion of these 'compensating' variables, allows us to distinguish between partial and total effect of amenities in explaining regional differences in SWB, providing insights into the extent to which specific local amenities have an additional effect on life satisfaction that is not compensated for by housing and labor markets.

The application of a two-step regression approach is common when the data have a

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[6] To aid interpretation and reduce the number of zeros after a decimal point, we applied a linear transformation and rescaled the estimated county-level fixed effects to stay within the range 0 to 100, where 0 corresponds to the least pleasant county.

[7] That is, we add individual income to the set of regressors X_{ijt} in the alternative specification of equation (1), and we add median housing values and median income at the county level to the county-level regressors Z_{jt} in equation (2).

hierarchical structure, as with multilevel modelling (Lewis and Linzer 2005), or more generally when a variable estimated in the first step (or its transformation) conveys information about a phenomenon of interest (Durnev et al. 2004, Greene et al. 2009). In our case, county dummies convey information about the desirability of living in a place which in turn can be explained by local amenities. Moreover, the two-step regression approach avoids collinearity problems that would arise in a single individual-level regression model including time-invariant county level regressors and county dummies.

We employ a two-pronged strategy to deal with the heteroscedasticity that might arise due to variation in the sampling variance of the estimated dependent variable. (For example, the reported LS in one county may be based on a larger sample and thus be a more precise estimation of SWB in that county compared to others with fewer observations.) First, we cluster standard errors at the county level in both the first and second step regressions. Clustering helps tackle heteroscedasticity (Lewis and Linzer, 2005) and accounts for the intra-county correlation structure of the regression residuals (due to individuals sharing county-level characteristics). Second, we exclude counties with fewer than 50 observations per year.[8]

We performed two additional robustness checks. First, given the categorical nature of the dependent variable in equation (1), life satisfaction, we estimated equation (1) using an ordered logit. As expected, there was little qualitative difference between the results of the cardinal and ordinal models (Ferrer-i-Carbonell and Frijters 2004, Angrist and Pischke 2009). Second, given

[8] This is consistent with the BRFSS guidelines of not reporting or interpreting FIPS County codes for any county with less than 50 respondents. 2010 SMART: BRFSS City and County Data and Documentation, Comparability of data: Retrieved from URL: http://www.cdc.gov/brfss/smart/2010/compare_10.pdf. To check the robustness of this choice, we estimated all the models excluding counties with less than 100 observations, and find consistent results with the original models.

the multi-level structure of the data, we estimated a random intercept model in which the intercept varies across counties, and the results were similar.

2.3 Data

Survey Data

Individual level data comprising life satisfaction scores and socio-demographic information (age, education, income, marital status, employment status, health status, sex) come from the BRFSS which is a state-based health survey conducted annually by the Centers for Disease Control and Prevention (CDC) to gather information on major behavioral risks among adults associated with premature morbidity and mortality. Data are collected for all 50 states. To ensure representativeness of the general U.S. population we used BRFSS-provided sampling weights across all estimations.[9]

Between 2005 and 2010 the questionnaire contained a standard 4-point scale life satisfaction question: “In general, how satisfied you are with your life?” Respondents could choose between the following categories: “very satisfied”, “satisfied”, “dissatisfied” or “very dissatisfied”. The average life satisfaction in the sample is 3.4, between “satisfied” and “very satisfied.”[10] Table 2.1 describes the variables and data sources, while Table 2.2 presents the summary statistics.

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[9] The assigned weight to each individual accounts for factors such as the number of adults in the household, number of residential telephone numbers in the household (BRFSS is a telephone survey) and probability of selection among the strata. Retrieved from URL: http://www.cdc.gov/brfss/annual_data/2010/2010_weighting.htm

[10] Few respondents report to be very dissatisfied (1%) or dissatisfied (4%), with most respondents in the satisfied (49%) and very satisfied (46%) categories.

Table 2.1: Variable definitions and data sources

Variable	Source	Description	Year	level
Individual level variables				
Life Satisfaction BRFSS		"How satisfied with life as a whole?": 4(Very satisfied); 3(Satisfied); 2 (Dissatisfied); 1 (Very dissatisfied)	2005-2010	Individual matched to county
Educational Level	BRFSS	Total years of schooling		
Household Income	BRFSS	8 categories: 1 (< $10K); 2 [$10K - $15K); 3 [$15K - $20K); 4 [$20K - $25K); 5 [$25K - $35K); 6 [$35K - $50K); 7 [$50K - $75K); 8 (>=$75K)		
Marital Status	BRFSS	6 categories: Married, Divorced, Widowed, Separated, Never married, Cohabiting		
Race	BRFSS	6 categories: White, Black/African American, Asian, Native Hawaiian/Pacific Islander, American Indian/Alaskan Native, Other		
Age	BRFSS	6 categories: 1(18 to 24); 2(25 to 34); 3(35 to 44); 4(45 to 54); 5(55 to 64); 6(65 or older)		
Employment Status	BRFSS	8 categories: Employed, Self-employed, Out of work > 1 year, Out of work < 1 year, Homemaker, Student, Retired, Unable to work		
General Health Status	BRFSS	5 categories: 1 (Poor); 2(Fair); 3(Good); 4(Very good); 5 (Excellent)		
Sex	BRFSS	Dummy: 1= Male		
Regional variables				
County Dummies		Estimated from the first step regression	2005-2010	County
Mean travel time to work	ACS-Census	Travel time to work in minutes	2005-2010	County
Income Tax	STC-Cencus	Per-capita income tax in 1000 dollars	2005-2010	State
Pupil Teacher Ratio	NEA	Ratio of pupil to teacher	2005-2010	State
Population Density	2010 Census	100 population per square mile	2010	County
Unemployment Rate	BLS	Unemployment rate	2005-2010	County
Median household Income	ACS-Census	Median Household income (‘000 US$)	2005-2010	County
Median house value	ACS-Census	Median house value (‘000 US$)	2005-2010	County
Urban Area (%)	RPA	Percentage of Urban area	2010	County

Metro statistical Area	OMB	Core urban area of 50,000 or more population	2005-2010	County
Micro statistical Area	OMB	Core Urban area of at least 10,000 and less than 50,000	2005-2010	County
Mean Max. July temp	NCDC	Mean of daily max. Temperature in July (°F)	2005-2010	County
Mean Min. Jan. temp	NCDC	Mean of daily min. Temperature in January (°F)	2005-2010	County
Precipitation	NCDC	Precipitation (both rain and snow) in inches	2005-2010	County
Mean Max. July temp. Normals	NCDC	Mean daily max. temp July (°F) - Normals 1981 - 2010	2005-2010	State
Mean Min. Jan. temp. Normals	NCDC	Mean daily min. temp. January (°F) - Normals 1981 - 2010	2005-2010	State
Precipitation Normals	NCDC	Precipitation (inches, rain and snow) - Normals 1981-2010	2005-2010	State
Mean Elevation	RPA	Mean elevation in meters	2010	County
# of Unhealthy Days	EPA	Total # of unhealthy air pollution days (all groups)	2005-2010	County
Federal Recreational Land (%)	RPA	Includes recreational land from BLM, USFS, National Park Service, and Fish & Wildlife Service	2010	County
Coastal Area	RPA	Dummy: 1= coastal	2010	County
Sunshine (%)	NCDC	% of sun radiation-Climatological Normals 1981 - 2010	-	State

Table 2.2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
First Step Regression individual level variables					
Life satisfaction	1,651,097	3.39	0.63	1	4
Education	1,651,097	14.12	2.10	0	16
Household Income					
Less than $10K	1,651,097	0.05	0.21	0	1
$10K- $15K	1,651,097	0.06	0.23	0	1
$15K-$20K	1,651,097	0.07	0.26	0	1
$20K-$25K	1,651,097	0.09	0.29	0	1
$25K- $35K	1,651,097	0.12	0.33	0	1
$35K- $50K	1,651,097	0.16	0.37	0	1
$50K-$75K	1,651,097	0.17	0.38	0	1
More than $75K	1,651,097	0.28	0.45	0	1
Marital Status					
Married	1,651,097	0.57	0.50	0	1
Divorced	1,651,097	0.15	0.35	0	1
Widowed	1,651,097	0.12	0.32	0	1
Separated	1,651,097	0.02	0.15	0	1
Never married	1,651,097	0.12	0.32	0	1
Cohabiting	1,651,097	0.02	0.15	0	1
Race					
White	1,651,097	0.84	0.37	0	1
Black or African American	1,651,097	0.08	0.28	0	1
Asian	1,651,097	0.02	0.14	0	1
Native Hawaiian/ Pacific Islander	1,651,097	0.00	0.05	0	1
American Indian/Alaskan Native	1,651,097	0.01	0.11	0	1
Other race	1,651,097	0.05	0.21	0	1
Age					
18 to 24	1,651,097	0.03	0.17	0	1
25 to 34	1,651,097	0.11	0.31	0	1
35 to 44	1,651,097	0.17	0.37	0	1

45 to 54	1,651,097	0.22	0.41	0	1
55 to 64	1,651,097	0.22	0.41	0	1
65 or older	1,651,097	0.27	0.44	0	1
Employment					
Employed for wages	1,651,097	0.47	0.50	0	1
Self-employed	1,651,097	0.09	0.28	0	1
Out of work for more than 1 year	1,651,097	0.02	0.14	0	1
Out of work for less that 1 year	1,651,097	0.03	0.16	0	1
Homemaker	1,651,097	0.07	0.26	0	1
Student	1,651,097	0.02	0.13	0	1
Retired	1,651,097	0.25	0.43	0	1
Unable to work	1,651,097	0.06	0.24	0	1
General health					
Poor	1,651,097	0.05	0.22	0	1
Fair	1,651,097	0.12	0.33	0	1
Good	1,651,097	0.30	0.46	0	1
Very good	1,651,097	0.33	0.47	0	1
Excellent	1,651,097	0.19	0.40	0	1
Sex					
Male	1,651,097	0.39	0.49	0	1
Second Step Regression regional variables					
Estimated County Dummies (with income)	7,474	53.24	12.18	0	100
Estimated County Dummies (without income)	7,474	44.34	11.11	0	100
Mean Travel Time to Work (min)	6,006	22.20	4.78	10.12	44.18
Income Tax (1,000 dollars per capita)	6,945	0.94	0.42	0.04	2.24
Pupil Teacher Ratio	7,474	15.26	2.35	9.20	25.60
Unemployment Rate	7,468	6.64	2.99	1.90	29.10
Population density (100 people/square mile)	7,474	5.34	26.86	0.01	694.68
Metropolitan area	7,474	0.57	0.50	0.00	1.00
Micropolitan area	7,474	0.27	0.45	0.00	1.00
Not Metropolitan/ Micropolitan area	7,474	0.16	0.37	0.00	1.00
Urban area land use (%)	7,401	14.15	17.33	0.00	98.08
Log of Median Household Income (1,000 $)	7,474	45.93	12.53	20.25	119.07

Median house value (1,000 dollars)	6,039	155.95	105.17	28.80	862.90
Mean Maximum July Temperature (°F)	7,474	83.87	5.59	38.30	97.05
Mean minimum January Temperature (°F)	7,474	25.34	10.49	4.28	63.81
Precipitation (inches)	7,474	37.67	13.08	1.52	82.61
Mean Maximum July Temperature Normals (°F)	7,468	86.63	5.01	71.7	98.6
Mean minimum January Temperature Normals(°F)	7,468	24.21	11.38	-9.2	51.4
Precipitation Normals (inches)	7,468	39.18	12.96	7.03	73.78
Mean Elevation (Meter)	7,474	422.54	538.35	0.12	3238.47
Unhealthy Day (#days)	4,539	8.33	17.06	0.00	245
Federal Recreational Land (%)	7,474	8.32	17.82	0	181.05
Coastal Area (1 if coastal)	7,474	0.31	0.46	0	1
Sunshine (%)	7,474	59.54	7.91	40.00	84.50

BRFSS individual-level survey data can be merged by either county or state Federal Information Processing Standard (FIPS) codes with local amenities at those levels.[11] We consider a range of local amenities that can be classified into two categories: 1) environmental and climate amenities (mean maximum July temperature, mean minimum January temperature, precipitation, percentage of sun radiation, being in the coast, elevation, and availability of national and state recreational services); and 2) other local public goods such as access to cultural and urban amenities and transportation infrastructure (ambient air quality, commuting time, unemployment rate, pupil-teacher ratio, population density, percentage of urban area, and level of urbanization based on Metropolitan/Micropolitan area definitions).

[11] The number of counties in the analysis varies with the econometric specification depending on the variables included in the regression. In the specification with the largest number of observations (7,474), the unbalanced panel of 1,658 counties includes 1,214 counties for 2005, 1,122 counties for 2006, 1,279 counties for 2007, 1,272 counties for 2008, 1,282 counties for 2009 and 1,305 counties for 2010. In the specification with the smallest number of observations (3,651), the unbalanced panel of 735 counties includes 499 counties for 2005, 497 counties for 2006, 653 counties for 2007, 667 counties for 2008, 659 counties for 2009 and 676 counties for 2010.

Environmental and climate amenities

In their hedonic analysis of climate, Rehdanz and Maddison (2009) find that individuals exhibit preferences for mild climates. They estimate negative implicit prices for July maximum temperatures and positive prices for January minimum temperatures. Correspondingly, we use two variables: average maximum July temperature and minimum January temperature. Other climate data include mean annual precipitation (in inches) and percentage of sunshine (average percent possible sun). January min temperatures, July maximum temperatures, and precipitation data are obtained from 7,835, 7,865 and 8,301 weather stations, respectively, from the National Climatic Data Center (NCDC) from 2005 to 2010. We applied the Inverse Distance Weighting (IDW) interpolation technique which explicitly assumes that things that are closer together are more alike than those farther apart, such that for predicting unmeasured weather information in a station, measured values in stations closest to the designated location have more influence on the predicted value than those farther away. [12] For counties for which information from more than one weather station were available, we took the average. Information on relative humidity is available from the EPA annual Airdata database. However, data are sketchy with many missing values which substantially reduced the estimation sample, and the variable was not found to be statistically significant so we did not include it in the models reported in the study.

Green spaces and the possibilities they offer for outdoor recreation contribute significantly to the physical, mental, and spiritual health of individuals (McKinney 1999, Thompson Coon et al. 2011, Clawson and Knetsch 2013) and have been shown to be positively correlated to self-reported life satisfaction (MacKerron and Mourato 2013, Diener et al. 2015). We control for the

[12] The optimal power for the interpolation is 2 based on root mean square prediction error.

percentage of federal recreational land at the county level from the US Forest Service Renewable Resources Planning Act (RPA) recreation supply amenities database which pools together data from the Bureau of Land Management, Forest Service, National Park Service, and the Fish and Wildlife Service.

Other local amenities

Urbanization can increase labor market productivity (Puga 2010), and living in or close to large urban areas facilitates access to cultural and recreational activities, and to an expanded choice of housing, schooling and consumption possibilities (Glaeser et al 2001, Albouy 2008). These potential benefits are often offset by congestion, commuting costs, pollution and crime, making it difficut to find the net effect of urbanization on SWB (Winter and Li 2016). Overall, residents of cities, especially in declining cities, appear to be less happy than other Americans (Glaeser et al. Winter and Li 2016).

To measure commuting costs we use travel time to work; the total number of minutes that it usually takes the person to get from home to work each day during the reference week. It is calculated by dividing the aggregate travel time for workers living in the county by the number of workers 16 years old and over who do not work at home, with data from the Census Bureau's Annual American Community Survey. Commuting, especially in the morning, is typically unpleasant and negatively correlated with life satisfaction (Kahneman and Krueger 2006, Stutzer and Frey 2008).

Air pollution, a particulary acute problem in urban areas, has been shown to negatively affect life satisfaction in a number of recent studies (Di Tella and MacCulloch 2008, Luechinger 2009, Levinson 2012, Ferreira et al. 2013). We use data from the EPA's ambient air quality index (AQI) that incorporates five criteria pollutants (ozone, particulate matter, carbon monoxide, sulfur dioxide and nitrogen dioxide) into a single index at the county level. It ranges from 0 (good air quality) to 500 (hazardous air quality). From the AQI, we calculate the "# of unhealthy days" equal to the sum of unhealthy days for sensitive groups (those with an AQI between 101 and 150), unhealthy days for the general population (AQI in the range 151- 200), and very unhealthy and hazardous days (AQI of 201 or higher). Two advantages of this variable are that (i) it includes unhealthy days for different groups in society and, thus, it can capture the effect on life satisfaction of worrying about others' health (e.g. family members); and (ii) it is publicly announced so that people are aware of it, and it potentially has a direct effect on life satisfaction in addition to an indirect effect through general health status.

In addition to controlling for the individual's employment status in the first step regression, in the second step we include the county's unemployment rate from the US Bureau of Labor Statistics. This is because people care about high rates of unemployment even when they themselves are not unemployed (Gallie and Russell 1998, Di Tella et al. 2001). The level of unemployment can affect the way in which the unemployed perceive their situation; it may reduce the stigma since they are less likely to blame themselves, or increase stress due to the difficulty of finding a new job.

Existing literature suggests that the second effect dominates; both, hedonic studies (Blomquist et al. 1988, Roback 1982) and studies that analyze SWB directly (Diener and Suh 1997, Ferreira and Moro 2010) estimate a negative impact of local unemployment rates on quality of life. However, the importance of controlling for unemployment is not restricted to it being a direct determinant of SWB. According to the crime literature (Allison 1972, Hsieh and Pugh 1993, Cornwell and Trumbull 1994, Fajnzlber et al. 2002, Burdett et al. 2003, Merlo 2003), local violent crime rates are affected by labor market outcomes proxied by county-level unemployment rates.

Data on violent crime rates from the FBI Uniform Crime Reports contain many missing values which reduced the sample substantially, so we use unemployment rates as a proxy instead.

Another common variable in hedonic studies ranking quality of life is the pupil-teacher ratio, which proxies for the quality of local school systems. We gathered it from the National Education Association's annual Rankings & Estimates reports.

Finally, we control for three indicators of urbanization at the county level: population density, percentage of urban area, and dummies for metropolitan and micropolitan areas, to help interpret the coefficients on the previous variables as partial effects. Population density (population in hundreds divided by county area in squared miles), is obtained from the 2010 Census. The percentage of urban area, from the Renewable Resources Planning Act (RPA) assessment, gives a relative measure of the extent of urbanization relative to other major land uses (cropland, pastureland, forest and rangelands).[13] Dummies for metropolitan and micropolitan statistical areas are based on the delineation by the Office of Management and Budget (OMB), where a metro area contains a Core Based Statistical Area of 50,000 or more population, and a micro area contains an urban core of at least 10,000 (but less than 50,000) population.

Compensating variables

In hedonic models, real housing prices and wages compensate for differences in amenities across locations. This suggests that part of the spatial variation in the residual life satisfaction unexplained by individual characteristics could be explained away by the inclusion of these "macro-level

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[13] The USDA Natural Resources Conservation Agency urban area definition includes residential, industrial, commercial, and institutional land; construction and public administrative sites; railroad yards, cemeteries, airports, golf courses, sanitary landfills, sewage plants, water control structures, small parks, and transportation facilities within urban areas.

compensating" variables. As we explained in section 2, we estimate an alternative version of equation (2) that considers two such variables: median housing values (excluding mortgages), and median income, both in real terms at the county level, and also control for per capita state income tax, with data collected from the US Census Bureau Annual American Community Survey and the US Census Bureau Annual Survey of State Government Tax Collections.

Social comparison effects have been found to be an important factor in the individual utility function (Clark and Oswald 1996, McBride 2001, Luttmer 2005, Clark et al. 2008). To the extent that county-level median income proxies for relative income, it can capture some of its (negative) effect on life satisfaction.

2.4 Results

First step regression

The first step life-satisfaction regression (1) controls for individual characteristics in order to obtain regression-adjusted measures of well-being in a particular year and county. Although the purpose of estimating (1) is to obtain the residual, county-level life satisfaction $\widehat{\delta_J}$, we start by discussing the coefficients on the individual-level variables in Table 2.3.[14] The difference between columns (1) and (2) is that column (2) includes individual income in the list of regressors.

Table 2.3: Individual level life satisfaction regression (first step regression)

	X_i does not include individual income	X_i includes individual income
Age (ref: 18-24)		
25 to 34	-0.061***	-0.050***
	(0.006)	(0.006)
35 to 44	-0.068***	-0.073***
	(0.007)	(0.007)
45 to 54	-0.054***	-0.065***

[14] The results for the multi-level regression are presented in appendix A.

	(0.006)	(0.006)
55 to 64	0.010*	0.002
	(0.005)	(0.006)
65 or older	0.071***	0.083***
	(0.006)	(0.006)
Education	-0.048***	-0.046***
	(0.004)	(0.004)
Education^2	0.002***	0.002***
	(0.001)	(0.001)
Marital status (ref: Never married)		
Married	0.218***	0.181***
	(0.004)	(0.0041)
Divorced	-0.005	0.004
	(0.004)	(0.004)
Widowed	0.056***	0.056***
	(0.004)	(0.005)
Separated	-0.065***	-0.055***
	(0.010)	(0.010)
Cohabit	0.078***	0.071***
	(0.006)	(0.006)
Employment status (Ref: Employed)		
Self-employed	-0.011***	-0.007*
	(0.004)	(0.004)
Unemployed-more than 1 year	-0.243***	-0.201***
	(0.007)	(0.007)
Unemployed-less that 1 year	-0.205***	-0.177***
	(0.007)	(0.007)
Homemaker	0.014***	0.030***
	(0.003)	(0.003)
Student	0.031***	0.034***
	(0.007)	(0.007)
Retired	0.034***	0.056***
	(0.003)	(0.004)
Unable to work	-0.216***	-0.176***
	(0.006)	(0.007)
General Health (ref: Poor)		
Fair	0.220***	0.223***
	(0.006)	(0.006)
Good	0.364***	0.355***
	(0.006)	(0.006)
Very good	0.537***	0.515***
	(0.007)	(0.007)
Excellent	0.680***	0.649***
	(0.008)	(0.008)
Race (ref: White)		
Black / African American	-0.011***	0.009*
	(0.004)	(0.005)
Asian	-0.061***	-0.053***
	(0.012)	(0.012)
Native Hawaiian/ Pacific Islander	-0.015	-0.009
	(0.021)	(0.022)

American Indian /Native Alaskan	-0.010	0.003
	(0.011)	(0.013)
Other	-0.019**	-0.001
	(0.008)	(0.008)
Sex (ref: Female)		
Male	-0.012***	-0.017***
	(0.002)	(0.002)
Income (Ref: less than $10K)		
$10K-$15K		0.016
		(0.010)
$15K-$20K		0.032***
		(0.008)
$20K-$25K		0.036***
		(0.008)
$25K-$35K		0.057***
		(0.007)
$35K-$50K		0.083***
		(0.009)
$50K-$75K		0.133***
		(0.009)
More than $75K		0.212***
		(0.010)
	Yes	Yes
Year Dummies	Yes	Yes
County Dummies		
Observations	1,874,518	1,651,097
Adjusted R-squared	0.1605	0.1691

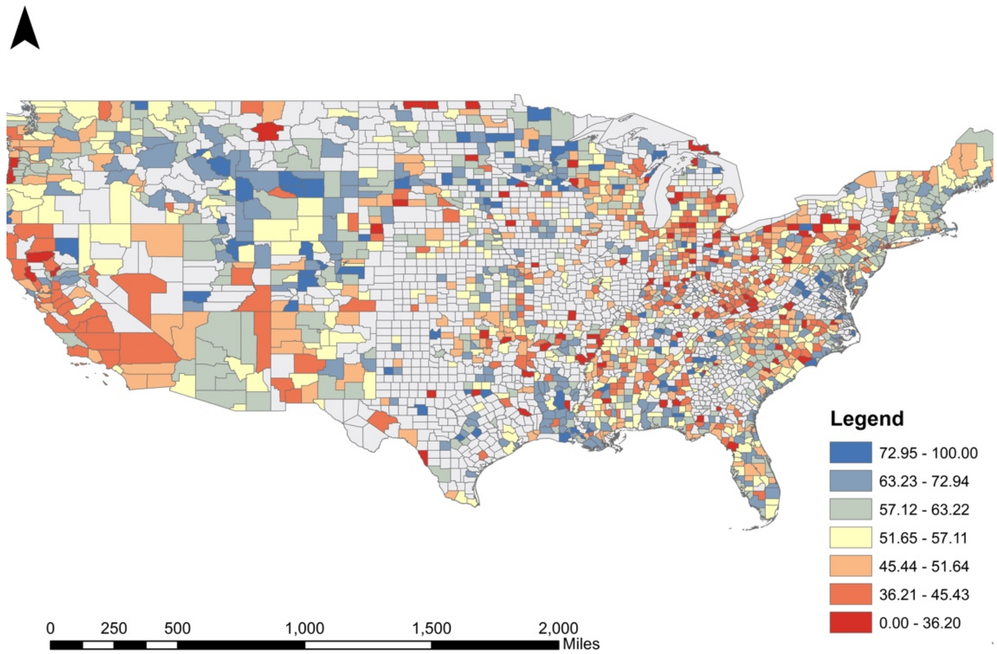
Notes: Clustered standard errors at county level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. As indicated in the table, both regressions include county and year dummies.

Consistent with previous literature, we find a U-shaped relationship between age and life satisfaction, with those 65 or older reporting the highest levels of life satisfaction. More years of schooling are associated with higher levels of life satisfaction in a non-linear fashion. Being separated is, as expected, negatively related to life satisfaction, and being married, widowed or cohabiting are positively related to life satisfaction, all relative to being single. One of the most negative correlates of life satisfaction is unemployment (with no evidence of adaptation to this situation from those who are long-term unemployed), and being unable to work, with an effect of between a fifth and a quarter of a life satisfaction category. Compared to those in poor health, those reporting other health categories fare better, and the impact monotonically increases with better health. Those with excellent health report two thirds of a life satisfaction category higher than those in poor health. African-American, Asian, and "other" report a lower level of life satisfaction than Whites. Males' life satisfaction is slightly lower than that of females.

Individual income enters in the regressions in column (2) in seven levels (each relative to an income of less than \$10,000). As expected, all the coefficients are positive, statistically significant (except for the \$10K-\$15K range), and increasing in income. Comparing columns (1) and (2) we observe that the signs of the coefficients are consistent across the models. The magnitudes are also very similar, even for unemployment, suggesting that the main impact of being unemployed is not the loss of income. A notable exception is for the African American dummy. It is negative and statistically significant in the specification that does not control for income, but switches sign after controlling for it. This suggests that part of the lower life satisfaction of African Americans compared to Whites during 2005 to 2010 can be explained by lower incomes.

Table 2.3 does not report the county dummy estimates ($\widehat{\delta_j}$), which represent the county-level adjusted life satisfaction; those are depicted in Figure 2.1. In addition, Tables 2.4 and 2.5 show the list of the 50 most and least satisfied counties, respectively.

A. Mean life satisfaction scores (Unconditional on socio-demographic characteristics)



B. Mean life satisfaction scores (Conditional on socio-demographic characteristics)

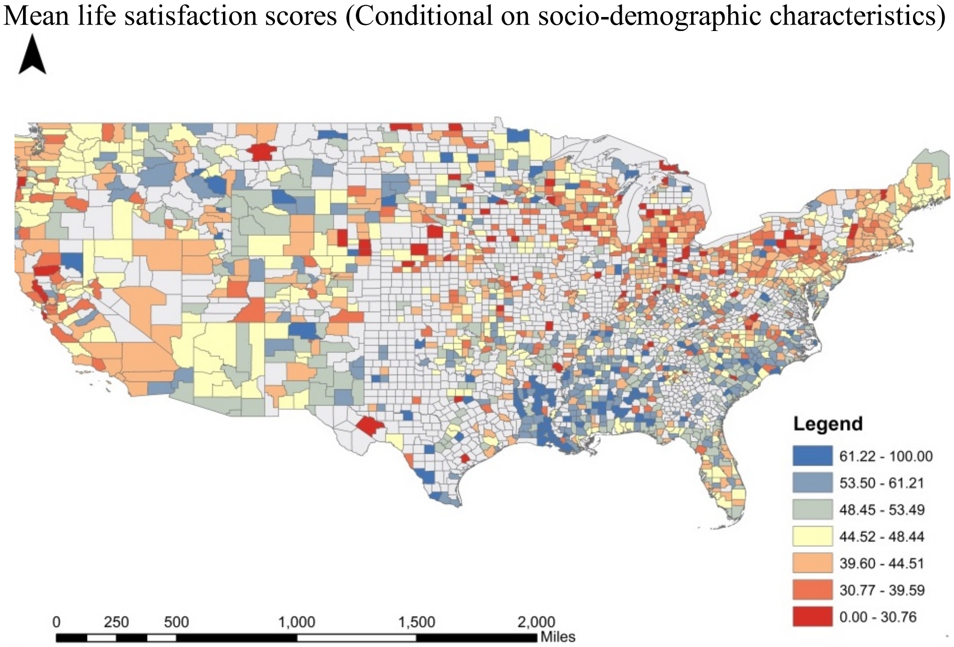


Figure 2.1: Life satisfaction scores across U.S. counties

Notes: County-level fixed effects are rescaled to stay within the range 0 to 100

The first panel in Figure 2.1 and the left half of Tables 2.4 and 2.5 show the unconditional rankings based on county dummy estimates from a life satisfaction regression that does not control for individual respondents' characteristics; that is, based on county-level unconditional mean life satisfaction. The second panel in Figure 2.1 and the right half of the tables show the conditional rankings based on county dummy estimates from a life satisfaction regression that controls for individual characteristics (i.e. equation 1), but not individual income. This is because when testing the equality of life satisfaction across counties, we let wages and rents vary to compensate for differences in amenities, and thus the set of individual characteristics X_{ij} in equation (1) does not include those two variables.

The rankings change depending on whether we condition for individual characteristics but not by much. In Table 2.4, four out of the nine counties ranked at the top, and 23 out of the 50 counties, appear in both columns of the table; that is, the ranking of the top counties does not change much after controlling for individual characteristics. Similarly, the conditional and unconditional rankings are similar for the unhappiest counties. In Table 2.5, out of the bottom 7 counties, 6 are in the two sides. Comparing Tables 2.4 and 2.5 also shows that there is much within-state variation in life satisfaction, which justifies a county-level analysis. Minnesota, for example has 2 out of the 20 most satisfied counties, but also 2 out of the 20 most unsatisfied counties in the U.S.

Table 2.4: Most satisfied counties

Mean life satisfaction (Unconditional-time adjusted) [(a)]			Mean life satisfaction (Conditional on socio-demographic characteristic-time adjusted) [(b)]		
State name	County name	Rank	State name	County name	Rank
Minnesota	Koochiching	1	Louisiana	Franklin	1
Texas	Ellis	2	Alabama	Geneva	2
Nebraska	Kimball	2	Louisiana	Winn	3
Minnesota	Pine	2	Louisiana	Grant	4
Idaho	Madison	5	Michigan	Alpena	5
Louisiana	Grant	6	Minnesota	Koochiching	6
Colorado	Summit	7	Nebraska	Kimball	7
Virginia	Rockingham	8	Illinois	Vermilion	8
Alabama	Geneva	9	Pennsylvania	McKean	9
Louisiana	Jackson	10	Virginia	Lynchburg City	10
North Carolina	Dare	11	Louisiana	St. martin	11
Idaho	Franklin	12	California	Lassen	12
Wyoming	Johnson	13	Montana	Deer Lodge	13
Virginia	Lynchburg City	14	Minnesota	Pine	14
South Dakota	Hand	15	Louisiana	Richland	15
Georgia	Forsyth	16	Alabama	Monroe	16
Georgia	Bartow	17	Georgia	Bartow	17
Minnesota	Clay	18	Louisiana	Jackson	18
Colorado	Routt	19	Louisiana	Evangeline	19
Minnesota	Redwood	20	Arkansas	Ouachita	20
Montana	Deer Lodge	21	Idaho	Madison	21
Michigan	Alpena	22	Alabama	Covington	22
Kentucky	Trigg	23	Alabama	Clarke	23
Minnesota	Goodhue	24	South Carolina	Hampton	24
Tennessee	Williamson	25	North Carolina	Dare	25
South Dakota	Lake	26	Kentucky	Harlan	26
Ohio	Union	27	Alabama	Dallas	27
Minnesota	Le Sueur	28	Virginia	Rockingham	28
Wyoming	Teton	29	Tennessee	Franklin	29
Texas	Tom Green	30	Louisiana	Morehouse	30
Virginia	Fairfax	31	Louisiana	Union	31
Kentucky	Oldham	32	Texas	Bastrop	32
Alabama	Limestone	33	Louisiana	Avoyelles	33
Indiana	Adams	34	Minnesota	Douglas	34
Minnesota	Douglas	35	Texas	Ellis	35
Utah	Summit	36	Alabama	Limestone	36
Pennsylvania	McKean	37	North Dakota	Barnes	37
Oklahoma	Roger Mills	38	Texas	Tom Green	38
North Dakota	Barnes	39	Louisiana	Sabine	39
Virginia	Suffolk City	40	Louisiana	Washington	40

Iowa	Sioux	41	North Carolina	Northampton	41
Colorado	Gunnison	42	Wyoming	Big Horn	42
Wyoming	Washakie	43	Pennsylvania	Jefferson	43
Utah	Wasatch	44	Wisconsin	Taylor	44
Virginia	Loudoun	45	south Dakota	Haakon	45
Wisconsin	Douglas	46	Alabama	Sumter	46
Colorado	Douglas	47	Alabama	Chilton	47
Texas	Hockley	48	Texas	Hockley	48
Alabama	Chilton	49	Louisiana	Vermilion	49
Idaho	Boundary	50	Mississippi	Covington	50

Note: a) Based on the estimated county dummies from a regression of life satisfaction scores on year dummies and county dummies. b) based on the estimated county dummies from a regression of life satisfaction scores on individual characteristics (except income) year dummies and county dummies (i.e. equation (1)).

Table 2.5: Least satisfied counties

Mean life satisfaction (Unconditional-time adjusted) [(a)]			Mean life satisfaction (Conditional on socio-demographic characteristic-time adjusted) [(b)]		
State name	County name	Rank	State name	County name	Rank
South Carolina	Calhoun	1668	Michigan	Emmet	1668
Indiana	Blackford	1667	Ohio	Guernsey	1667
Ohio	Guernsey	1666	South Carolina	Calhoun	1666
New York	Chemung	1665	Minnesota	Nobles	1665
Indiana	Marshall	1664	Indiana	Marshall	1664
Michigan	Emmet	1663	New York	Chemung	1663
Minnesota	Nobles	1662	Iowa	Crawford	1662
Pennsylvania	Potter	1661	Ohio	Huron	1661
California	Tehama	1660	Indiana	Jay	1660
Indiana	Jay	1659	Texas	Pecos	1659
West Virginia	Wyoming	1658	Indiana	Knox	1658
California	Lake	1657	North Dakota	Pembina	1657
Iowa	Crawford	1656	Nebraska	Morrill	1656
Arkansas	Arkansas	1655	Missouri	Caldwell	1655
Indiana	Knox	1654	Montana	Fergus	1654
Ohio	Huron	1653	California	Lake	1653
Missouri	Howell	1652	Wisconsin	Kewaunee	1652
Missouri	Caldwell	1651	Minnesota	Brown	1651
Alabama	Butler	1650	Tennessee	Warren	1650
Louisiana	La Salle	1649	New York	Columbia	1649
Kentucky	Hart	1648	Michigan	Branch	1648
Michigan	Branch	1647	Wisconsin	Buffalo	1647
Montana	Fergus	1646	Ohio	Wood	1646
West Virginia	Braxton	1645	Virginia	Bedford	1645
Indiana	Jefferson	1644	Indiana	Steuben	1644
Pennsylvania	Warren	1643	South Dakota	Marshal	1643

Georgia	Decatur	1642	Ohio	Miami	1642
North Carolina	Columbus	1641	Nebraska	Holt	1641
South Dakota	Marshall	1640	Ohio	Clermont	1640
Texas	Angelina	1639	Illinois	Macon	1639
Virginia	Tazewell	1638	California	Tehama	1638
Wisconsin	Kewaunee	1637	Nebraska	Frontier	1637
Ohio	Ashtabula	1636	Michigan	Mason	1636
Nebraska	Morrill	1635	Kansas	Bourbon	1635
Texas	Johnson	1634	Missouri	Howell	1634
New York	Bronx	1633	Indiana	Dearborn	1633
New York	Kings	1632	Indiana	Jefferson	1632
West Virginia	McDowell	1631	New York	Rensselaer	1631
North Carolina	Anson	1630	Iowa	Boone	1630
Illinois	Macon	1629	Arkansas	Arkansas	1629
South Dakota	Bennett	1628	Texas	Victoria	1628
Georgia	Barrow	1627	Michigan	Chippewa	1627
Virginia	Henry	1626	Nebraska	Cheyenne	1626
Pennsylvania	Elk	1625	West Virginia	Braxton	1625
Michigan	St Joseph	1624	Georgia	Barrow	1624
Texas	Taylor	1623	Ohio	Clark	1623
Wisconsin	Wisconsin buffalo	1622	Michigan	Isabella	1622
Pennsylvania	Philadelphia	1621	Ohio	Hancock	1621
Virginia	Wise	1620	Oregon	Tillamook	1620
Arkansas	Poinsett	1619	Pennsylvania	Potter	1619

Note: a) Based on the estimated county dummies from a regression of life satisfaction scores on year dummies and county dummies. b) based on the estimated county dummies from a regression of life satisfaction scores on individual characteristics (except income) year dummies and county dummies (i.e. equation (1)).

Figure 2.2 shows the distribution of these adjusted life satisfaction estimates and gives some indication of the magnitude of the effects. Compared to living in the reference county (Autaga county in Alabama), living in the unhappiest county (Emmet county in Michigan) is associated with a drop in life satisfaction of 0.434 (p-value < 0.0001), while living in the happiest county (Franklin county in Louisiana) is associated with an increase in life satisfaction of 0.183 (p-value < 0.0001). These are large effects; for comparison, the point estimate of being unemployed in Table 2.3 was in the 0.2 range.

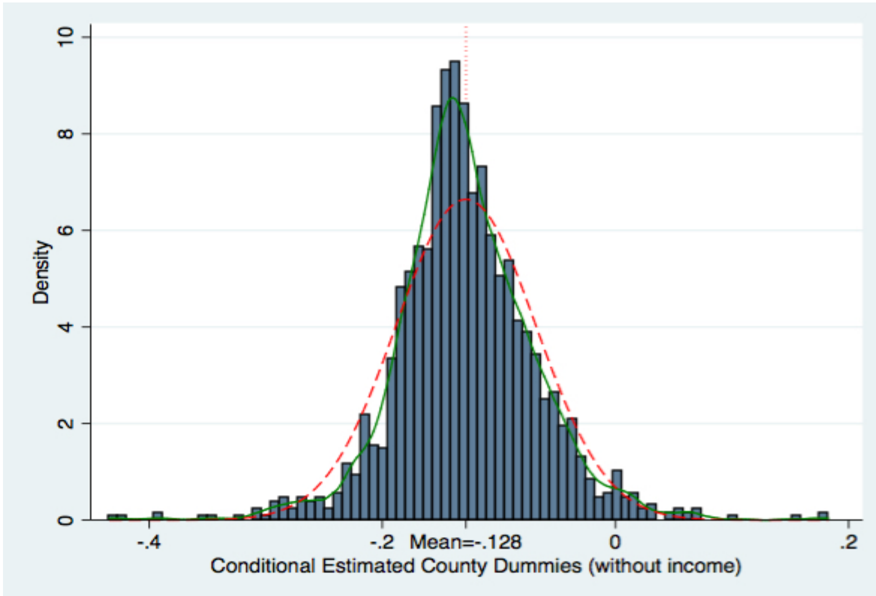


Figure 2.2: Distribution of county's adjusted life satisfaction

We formally test and reject the null hypothesis of equal life satisfaction across counties. The F-statistic of joint significance of the county dummies in the unconditional life satisfaction regression is F (5, 1668) = 818.92 (p-value < 0.0001), and in the conditional life satisfaction regression it is F (34, 1668) = 51708.60 (p-value < 0.0001). We also test the equality of both conditional and unconditional SWB across counties using the Kruskal-Wallis test and reject the null hyphothesis of equal SWB (in each case, p-value < 0.0001). Note that, as indicated above, in both conditional and unconditional tests we let wages and rents vary (i.e. income and housing price variables are not included in the first-step regression from which dummies are extracted). This suggests that these compensating factors are not eliminating the differences in life satisfaction across locations.

Second-step regression

Do environmental factors help explain differences in SWB across the US? Table 2.6 shows that they do. Column (1) - (3) show results of the estimation of equation (2) without state fixed effects while columns (4) - (6) include state fixed effects, that is they rely exclusively on within-state variation to identify the impact of amenities on residual life-satisfaction. Given the variation in life satisfaction scores across counties even in the same state (as hinted by Figure 2.1 and Tables 2.4 and 2.5), it is not surprising that some regressors (although not the climate variables) retain their significance in specifications with state dummies. Three explanatory variables: the student-teacher ratio, the percentage of sunshine, and income tax are measured at state level and their variation is captured by state fixed effects and time dummies; we therefore exclude them from the last three models. The model fit, as measured by the Bayesian Information Criterion (BIC) reported in the last row of the Table, is better for regressions without state dummies in two out of the three comparisons. We note that the regressions do not include county fixed effects. This is because we are interested in explaining the variation of life satisfaction across (not within) counties.

Table 2.6: County level life satisfaction regression (second step regression)

	(1)	(2)	(3)	(4)	(5)	(6)
	Env. and climate amenities	All amenities	All amenities	Env. and climate amenities	All amenities	All amenities
VARIABLES	Without compensating factors	Without compensating factors	With micro & macro compensating factors	Without compensating factors	Without compensating factors	With micro & macro compensating factors
Mean Min. Jan Temp.	0.117***	0.139***	0.150***	-0.076***	0.010	0.006
	(0.013)	(0.018)	(0.024)	(0.024)	(0.027)	(0.033)
Mean Max. Jul Temp.	-1.250***	-1.499***	-1.887***	-0.266	-0.403	-0.277
	(0.364)	(0.511)	(0.671)	(0.400)	(0.567)	(0.677)
Mean Max. Jul Temp.^2	0.008***	0.009***	0.012***	0.002	0.003	0.002
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Precipitation	0.068***	0.043***	0.049***	-0.001	0.010	-0.002
	(0.010)	(0.013)	(0.016)	(0.011)	(0.014)	(0.016)
Federal recreation land	0.001	0.001	0.035***	0.011	0.008	0.016
	(0.008)	(0.010)	(0.013)	(0.008)	(0.009)	(0.010)
Coastal	-0.798***	-0.783**	-0.595	0.442	0.243	0.548
	(0.272)	(0.320)	(0.402)	(0.334)	(0.383)	(0.437)
Mean elevation	0.001***	0.001**	0.001*	-0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sunshine	0.064***	0.056***	0.070***			
	(0.016)	(0.018)	(0.026)			
Unhealthy day		-0.013**	-0.017**		-0.001	-0.004
		(0.007)	(0.007)		(0.007)	(0.008)

Mean travel		0.007	-0.025		-0.012	-0.093**
time to work		(0.031)	(0.042)		(0.033)	(0.041)
Unemployment		-0.158**	-0.120		-0.071	0.076
rate		(0.075)	(0.100)		(0.083)	(0.104)
Population		-0.011***	-0.004		-0.004*	0.001
density		(0.003)	(0.003)		(0.002)	(0.003)
Urban area (%)		-0.031***	-0.047***		-0.036***	-0.054***
		(0.007)	(0.008)		(0.007)	(0.009)
Metropolitan		-1.976***	-3.760***		-1.281**	-2.808***
area		(0.613)	(0.712)		(0.582)	(0.606)
Micropolitan		-1.380**	-2.387***		-0.651	-1.55**
area		(0.637)	(0.756)		(0.595)	(0.628)
Pupil-teacher		-0.288***	-0.251***			
ratio		(0.065)	(0.081)			
log (median hh			0.010			0.001
income)			(0.022)			(0.020)
Median			-0.010***			-0.004
housing value			(0.003)			(0.003)
Income tax			-0.126			
			(0.518)			
Year (*Ref: year 2005)*						
Year 2006	6.911***	6.592***	4.660***	7.914***	7.387***	5.594***
	(0.305)	(0.392)	(0.472)	(0.324)	(0.418)	(0.472)
Year 2007	-1.803***	-2.170***	2.835***	-2.179***	-2.197***	2.917***
	(0.307)	(0.386)	(0.470)	(0.302)	(0.383)	(0.431)
Year 2008	-1.983***	-2.033***	-0.072	-2.319***	-2.030***	-0.124
	(0.303)	(0.399)	(0.478)	(0.304)	(0.404)	(0.466)
Year 2009	-15.535***	-15.261***	-16.644***	-16.245***	-15.807***	-17.655***
	(0.301)	(0.491)	(0.634)	(0.310)	(0.498)	(0.607)
Year 2010	-10.684***	-10.022***	-4.920***	-11.250***	-10.568***	-6.147***
	(0.304)	(0.516)	(0.661)	(0.304)	(0.536)	(0.648)
Constant	86.783***	104.539***	129.317***	66.723***	67.127***	73.643***
	(14.95)	(20.715)	(27.458)	(16.247)	(23.226)	(27.774)
State F.E	No	No	No	Yes	Yes	Yes
Observations	7474	3999	3651	7492	4017	4017
Adjusted R^2	0.486	0.556	0.515	0.525	0.582	0.544
BIC	52338	26995	25653	52224	27191	28242

Notes: Clustered standard errors at county level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable in columns (1), (2), (4) and (5) is county-adjusted life satisfaction from a first step regression that does not control for income and dependent variable in columns (3) and (6) is county-adjusted life satisfaction from a first step regression that controls for income.

The first column in Table 2.6 shows that environmental and climate amenities and time dummies explain a sizeable fraction (49%) of the variation in county-level regression-adjusted life satisfaction. Because the dependent variable in this regression, county level life satisfaction, is from a first step regression that does not control for factors that compensate for differences in amenities across locations, i.e. it does not control for income or rents, and these variables are not included as additional covariates in the second step regression, either, the coefficients capture the *total* rather than the partial effect of environmental amenities on SWB.

To allow for possible nonlinearities in the impact of environmental amenities on well-being (Albouy et al. 2016), we tested the significance of a quadratic form for each amenity. It was rejected except for maximum July temperature. Regarding the impacts of specific variables, the mean minimum January temperate exhibits a significant positive effect on well-being. With a turning point of 80 (°F), the impact of the maximum mean July temperature is also positive suggesting that warmer places in the US report to be happier.[15] The precipitation indicator is also statistically significant and positive in the first three columns. As one would expect, the effects of these three climate variables are weakened in specifications that include state fixed effects.

We further explored the hypothesis that the effect of weather and climate variables depends on their variability and, in particular, on whether they deviate from their long-run normal. We thus estimated an additional regression, reported in Table 2.7, in which we substitute the climate and weather variables (minimum January temperature, maximum July temperature and precipitation) with their deviation from the climatological Normals for 1981 to 2010. The results indicate that

[15] The nature of the dependent variable, *annual* average county-level life satisfaction, prevents us from investigating further the distribution and the impact of extreme temperature and weather events.

for all three variables, their deviation from the normal (taken to be an indicator of average long-run climatic conditions) are negatively associated with residual county-level life satisfaction.

Table 2.7: Climate amenities deviation from Normals (second step regression)

	Environmental and climate amenities
	Deviation from Normals
Mean Min. Jan Temp.	-0.173***
	(0.027)
Mean Max. Jul Temp.	-0.080***
	(0.026)
Precipitation	-0.025*
	(0.013)
Federal recreation land	0.024***
	(0.009)
Coastal	-0.446
	(0.289)
Mean elevation	-0.002***
	(0.001)
Sunshine	0.118***
	(0.015)
Constant	41.897***
	(0.895)
Year dummies	Yes
State fixed effects	No
Observations	7,468
Adjusted R-squared	0.476
BIC	-14170

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

Column (2) of Table 2.6 includes other environmental and local disamenites induced by urbanization. Air pollution, measured by the number of unhealthy days, and congestion, measured by commuting time, are two examples of negative externalities of urbanization in populated areas. Interestingly, the number of unhealthy days has a negative impact on life satisfaction even after controlling for several variables related to urbanization. Commuting time on the other hand is insignificant in all models. We note that these results do not seem to be driven by multicolinarity among the regressors. The variance inflation factors (VIFs) for all the coefficients in column (2) – except for July temperature, which enters in a quadratic form – are between 1.18 and 4.87, well below 10 which is taken as the rule of thumb value indicating high multicolinearity. For mean travel time to work, in particular, the VIF is 1.37. Being in a coastal county has a negative effect on life satisfaction in both columns (1) and (2). Although this may seem surprising, we note that these regressions do not control for some factors (in particular higher rents) associated with living in more desirable coastal areas.

Column (3) in Table 2.6 reports the results from specifications that do include these compensating factors. After holding individual income constant (by using county dummies in a first step regression that controls for individual income) and controlling for county-level median household income, median housing values, and for differences in state income tax, which we refer to as *macro-level compensating factors*, the negative effect of living in coastal areas fades away. Consistent with this result, mean elevation which was positive and significant in columns (1), (2) and (3) drops in statistical significance. On the contrary, the percentage of federal recreational land becomes statistically significant (with a positive effect) in column (3), while sunshine and other climatic variables have robust effects across models.

County-level unemployment and population density are negatively related to life satisfaction in column (2) of Table 2.6, but stop being significant in column (3) after controlling for individual's income and the county's median household income, median housing values, and the per capita income tax. The negative effect of other indicators of urbanization: living in a metropolitan or in a micropolitan area, intensify when we control for compensating factors, with metropolitan areas showing a more negative effect than micropolitan areas. These results are consistent with the observation by Winters and Li (2016) that the impacts of urbanization on life satisfaction are non-linear and that a simple population density indicator may miss this non-linearity. They are also consistent with the fact that incomes in large cities are higher on average. As hypothesized, higher pupil-teacher ratios have a negative impact on life satisfaction.

Interurban hedonic models predict that areas with better amenities for firms and individuals will have higher housing prices. A higher level of a productive amenity would attract individuals and firms and this would bid up the price of property. The impact on wages is ambiguous depending on whether individuals' labor supply outstrips or not firms' demand. Regarding their impact on utility, in column (3) we estimate a negative relationship between higher housing values and SWB. Consistent with a positive impact of individual wages on utility, the second column in Table 2.3 reported positive coefficients for the individual income variables. Median county income, on the other hand, is statistically insignificant in column (3). Deaton and Stone (2013) argue that the level of aggregation matters when estimating the relationship between SWB and income, due to the importance of both absolute and relative income effects on individual well-being. They suggest that the coefficient on county average income is the difference between the individual and group income coefficients in an individual-level regression. The insignificant coefficient on median county income in our model is thus consistent with a negative relative income effect that results in a zero net effect, but because we are implicitly controlling for individual income, an alternative explanation is that higher county income finances higher levels of public goods which positively impact LS (conditional on income taxes), countervailing the negative effect of relative income.

The comparison of columns (2) and (3) offers other important insights. While labor and housing markets seem to be compensating for living in coastal counties, in counties with larger recreational lands and to some extent for living in larger cities, the coefficients for the climate and pollution variables are similar across models. This similarity between total and partial effects suggests a lack of capitalization for these amenities. The comparison of columns (5) and (6), that include state fixed effects, suggest that, in addition to recreational lands, labor and housing markets are compensating for mean travel to work. We note, however, that columns (5) and (6) exploit only within-state variation to identify the effect of local amenities on regression-adjusted life satisfaction across counties, and many of the amenities that were statistically significant in columns (2) and (3) lose their significance.

To check the robustness of the results to the estimation method, we present the multi-level regression results in appendix A. As expected, the signs of the estimated coefficients are similar to those in Table 2.6. Differences in the size of the estimates are due to the rescaling of the county-level adjusted life satisfaction to be in the range 0-100 in the second step regression. Consistent with what we found in the two-step regression model, the estimated random intercept model shows that there is a within-state variation in LS such that we observe significant between-county variation in LS of residents of a same state.

2.5 Discussion

Promoting human well-being and improving quality of life are fundamental objectives of public policy. While conventional indicators of economic performance, most notably GDP, can provide useful information on a society's standard of living, there is a growing consensus among policymakers and academics alike that more relevant indicators of social progress are needed (Stiglitz et al. 2009). For example, in 2010 David Cameron launched the National Wellbeing Programme in the UK to "start measuring our progress as a country, not just by how our economy is growing, but by how our lives are improving; not just by our standard of living, but by our quality of life." Since then, the UK's Office for National Statistics has developed and published a measurement framework comprising objective measures of wellbeing, like life expectancy or levels of unemployment, but also subjective measures – of how people actually feel, including overall satisfaction with life and happiness.

In this context, it is important to improve our understanding of SWB and to shed light on some unresolved puzzles. A vast literature has examined the most famous puzzle, the Easterlin paradox, that while income has a positive impact on SWB at a point in time, there is little effect of economic growth. Another puzzle that has received considerably less attention, and that is the subject of this paper, concerns the existence of large spatial variations in SWB across, but also within countries. In a spatial equilibrium, differences in utility across locations should be eliminated by labor and housing market price differentials.

In this paper we show that SWB does vary widely across counties in the U.S. and this is the case even after controlling for the individual characteristics of those living in different places. We reject the equality of life satisfaction across counties in specifications that let wages and rents vary across locations, which suggests that housing and labor markets are not fully compensating for differences in local amenities. We note that although we account for observable individual characteristics, the data do not allow to control for unobserved individual heterogeneity, and people can sort into places that are consistent with their tastes. However, Glaeser, Gottlieb, and Ziv (2014) present suggestive evidence that differences in happiness across metropolitan areas reflect more than the selection of unhappy people into unhappy places. Moreover, if people sorted into their prefered places, this would tend to equalize life satisfaction across space, and we do not observe this.

As for the factors that explain the differences in quality of life across U.S. counties, we consider a wide range of local amenities including climate, geographic characteristics, air pollution and other local public goods related to urbanization (most of them at the county level). We show that these local amenities explain a non trivial fraction of the variation in regression-adjusted county life satisfaction, that is, in the level not explained by individual personal characteristics. This is important because the impacts of environmental quality on well-being provide a major rationale for environmental management and regulation.

CHAPTER 3

WELL-BEING EFFECTS OF EXTREME WEATHER EVENTS IN THE UNITED STATES

3.1 Introduction

The interest of economists in studying the impacts of natural disasters on human well-being is not new but has intensified in recent years due to an increase in their incidence and damages. Between 2005 and 2014 the global disaster database EM-DAT recorded an annual average of 380 natural disasters worldwide caused by earthquakes, tsunamis, volcanic eruptions, hurricanes, floods and droughts (among others), which claimed almost 76,500 lives and affected 199.2 million people on average each year. Of these natural disasters, 335 (or 88%) were climate-related, an increase of 14% from the previous decadal average (CRED and UNISDR 2015). Weather and climate disaster time series from 1980-2011 in the U.S. also suggest increasing trends in both the annual frequency and aggregate losses of "billion-dollar" disasters (Smith and Katz 2013), with climate change expected to further increase the frequency, intensity, and duration of extreme weather events (IPCC 2013). In 2017 there were 16 billion-dollar disasters in the U.S. including three hurricanes –Harvey, Irma and Maria- with combined damages estimated at a record $306.2 billion (NCEI 2017).

In addition to more prevalent natural hazards, the concentration of population and physical structures in hazardous areas contributes to larger impacts of disasters on human well-being. Some impacts, such as the financial losses associated with property damages and the fiscal consequences of reconstruction, are tangible and can be easily quantified. However, natural disasters can also cause stress and other psychological costs (uncertainty, grief for the bereaved, individual and collective traumas) (Carroll et al. 2009, Luechinger and Raschky 2009). These intangible costs are clearly very important but are unaccounted for in official economic estimates of disaster damages.[16]

Psychologists recognize the need for immediate mental health aid after natural disasters. Public health scientists hypothesize a direct link between acute weather disasters and mental health by exposing people to trauma, and an indirect link by affecting physical health and community well-being (Berry et al. 2010). Regarding the direct link, most prior studies focus on whether the individual experienced the disaster-related traumatic events or stressors and if she has Post-Traumatic Stress Disorder (PTSD), which is the central psychopathology in the aftermath of disasters (Norris et al. 2002, Galea et al. 2005, Lowe et al. 2005, Neria et al. 2008, Fergusson et al. 2014).[17] In their review of 116 studies from 40 natural disasters between 1963 and 2005, Neria et al. (2008) concluded that the prevalence of PTSD in affected communities in the first 1-2 years after natural disasters ranges from 0.7% to 60% depending on the degree of exposure (Canino et al. 1990, Najarian et al. 1996). However, it is difficult to quantify the economic significance of these findings. Moreover, the effects of a disaster on the subjective well-being of individuals in affected communities go beyond those to the directly impacted. They include the impacts to their friends, relatives, first responders all the way to individuals experiencing distress after seeing or

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

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

hearing media reports (Cohen 2002).

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

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

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

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

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

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

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

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

The rest of the chapter proceeds as follows: Section 2.2 describes the data used in the analysis; Section 2.3 presents the quasi-experimental design to identify the impact of disasters on SWB and the econometric models. Section 2.4 contains the main estimation results and robustness checks. Section 2.5 presents additional analyses on the role of public and private risk transfer mechanism to mitigate disaster impacts, and on the effect of disasters on alternative indicators of SWB. Section 2.6 concludes.

3.2 Data

Individual level data comprising SWB scores and socio-demographic information (age, education, income, marital status, employment status, health status, sex) come from the BRFSS, which is a state-based health survey conducted annually by the Centers for Disease Control and Prevention (CDC) to gather information on major behavioral risks among adults associated with premature morbidity and mortality. Data are collected for all 50 U.S. states. Between 2005 and 2010 the questionnaire contained a standard 4-point scale life satisfaction question that we use as a measure of SWB: "In general, how satisfied you are with your life?" Respondents could choose between the following categories: "very satisfied", "satisfied", "dissatisfied" or "very dissatisfied". The average life satisfaction in the sample is 3.4, between "satisfied" and "very satisfied." Table 3.1 presents summary statistics of the life satisfaction question and other individual socio-demographic controls included in the regressions.

Table 3.1: Summary statistics of individual characteristics and disaster variables

	Mean	Std. Dev.	Min	Max
Panel A: Individual characteristics (BRFSS)[(a)]				
Life satisfaction *(Ordered variable)*	3.39	0.63	1	4
Education	14.09	2.11	0	16
Household Income (Continuous variable)	50364.31	29496.11	4676.24	98709.21
Marital Status (Categorical variable)				
Married	0.568	0.495	0	1
Divorced	0.145	0.353	0	1
Widowed	0.121	0.326	0	1
Separated	0.022	0.145	0	1
Never married	0.118	0.323	0	1
Cohabiting	0.024	0.153	0	1
Race (Categorical variable)				
White	0.840	0.366	0	1
Black or African American	0.081	0.274	0	1
Asian	0.018	0.133	0	1
Native Hawaiian/ Pacific Islander	0.002	0.046	0	1
American Indian/Alaskan Native	0.013	0.114	0	1
Other races	0.044	0.206	0	1

Age (Categorical variable)				
18 to 24	0.031	0.172	0	1
25 to 34	0.106	0.307	0	1
35 to 44	0.164	0.371	0	1
45 to 54	0.215	0.411	0	1
55 to 64	0.216	0.412	0	1
65 or older	0.266	0.442	0	1
Employment (Categorical variable)				
Employed for wages	0.471	0.500	0	1
Self-employed	0.087	0.281	0	1
Out of work for more than 1 year	0.020	0.141	0	1
Out of work for less that 1 year	0.025	0.156	0	1
Homemaker	0.071	0.257	0	1
Student	0.016	0.125	0	1
Retired	0.248	0.432	0	1
Unable to work	0.061	0.240	0	1
General health (Categorical variable)				
Poor	0.054	0.224	0	1
Fair	0.124	0.330	0	1
Good	0.298	0.458	0	1
Very good	0.333	0.471	0	1
Excellent	0.191	0.393	0	1
Mental health (Binary variable)				
Good (0 days of poor mental health)	0.667	0.471	0	1
Fair/Poor (1 and more days of poor mental health)	0.332	0.471	0	1
Sex (Dummy variable)				
Male	0.389	0.487	0	1
Health Care Access (Dummy variable)				
Health Care Access	0.896	0.305	0	1
Panel B: Disaster variable (NCEI)[(b)]				
Disaster dummy (=1 if disaster in last k months)				
Disaster (2 months)	0.09	0.28	0.00	1.00
Disaster (4 months)	0.17	0.37	0.00	1.00
Disaster (6 months)	0.25	0.43	0.00	1.00
Disaster (8 months)	0.32	0.47	0.00	1.00
Disaster (10 months)	0.39	0.49	0.00	1.00
Disaster (12 months)	0.44	0.50	0.00	1.00
Disaster (18 months)	0.58	0.50	0.00	1.00
Disaster dummy (=1 if disaster happened k-(k+2) months ago)				
Disaster (0-2 months)	0.09	0.28	0.00	1.00
Disaster (2-4 months)	0.09	0.29	0.00	1.00
Disaster (4-6 months)	0.10	0.30	0.00	1.00
Disaster (6-8 months)	0.10	0.30	0.00	1.00

Disaster (8-10 months)	0.10	0.30	0.00	1.00
Disaster (10-12 months)	0.10	0.30	0.00	1.00
Disasters by type in cumulative 6- and 8-months time windows				
Tropical cyclone (6 months)	0.03	0.18	0.00	1.00
Tropical cyclone (8 months)	0.05	0.21	0.00	1.00
Severe storm (6 months)	0.11	0.31	0.00	1.00
Severe storm (8 months)	0.14	0.35	0.00	1.00
Flood (6 months)	0.02	0.15	0.00	1.00
Flood (8 months)	0.03	0.18	0.00	1.00
Drought (6 months)	0.08	0.27	0.00	1.00
Drought (8 months)	0.10	0.30	0.00	1.00
Wildfire (6 months)	0.02	0.15	0.00	1.00
Wildfire (8 months)	0.03	0.18	0.00	1.00
Freeze (6 months)	0.02	0.13	0.00	1.00
Freeze (8 months)	0.02	0.15	0.00	1.00

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

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

BRFSS contains information on the exact day of the interview.

During the period of analysis (2004-2010), there were 11,969 episodes of severe weather and climate caused by forty-two "billion-dollar" disasters in the U.S.[18] classified by the NCEI as tropical cyclone, severe storm, flooding, drought, freeze and wildfire. The billion-dollar disaster database reports the time of occurrence and the states affected by the weather and climate events of greatest economic impact, based on the number of deaths and estimated monetary damages (Appendix B). We complement this information with the storm events database of NCEI to identify the counties affected by all the events associated with the disasters. Each disaster contains a series of events. For example, a severe storm may comprise tornado, thunderstorm wind, strong wind, high wind, hail, flash flood, flood and heavy rain events occurring across multiple locations at different times.[19] The classification of an event into a given disaster type is based on the "event or episode narrative" provided in the storm event database, NOAA Hurricane Center's definition of hazards associated with hurricanes, and Smith and Katz's (2013) specification of disasters types. We reduce the measurement error in combining the billion-dollar disasters and storm event dataset by using the exact date of the disaster as a complementary selection criterion. Appendix B reports the month (or in some cases the season) in which the disaster happened, but for the econometric analysis, we assign an exact disaster date to each affected county, based on the event and episode unique identification numbers. In all the cases, this is the day in which the event ends.

The second panel of Table 3.1 presents the descriptive statistics of the disaster variables.

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

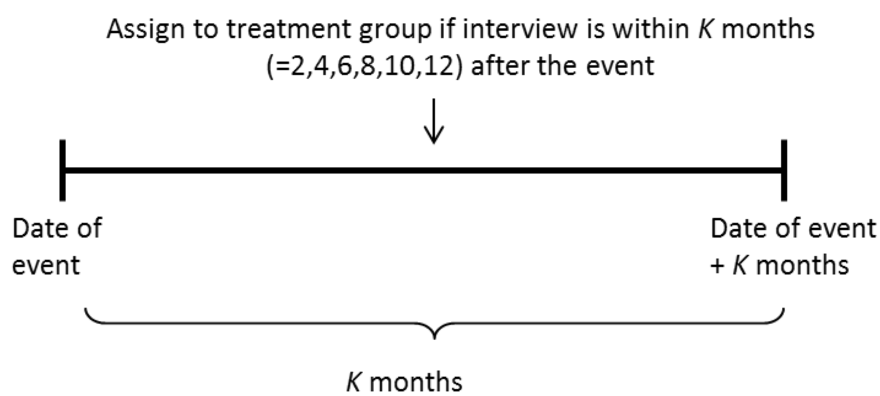
[19] Likewise, a tropical cyclone may contain episodes of flash flood, flood, heavy rain, high wind, hurricane (typhoon), storm surge/tide, rip current, strong wind, tornado, tropical depression and storm; a flood may contain episodes of flash flood, flood, heavy rain, and lakeshore flood; a drought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

Nine percent of the respondents live in counties that were affected by one disaster in the two months preceding the interview (variable "Disaster (2 months)"), and the percentage increases to forty-four in the previous year (variable "Disaster (12 months)"). Among disasters, severe storms are the most common type.

3.3 Identification strategy and econometric model

Although we are using observational data, randomization is done by nature in that extreme weather events act as exogenous shocks randomly assigning individuals into treatment or control groups. The identification strategy is based on two dimensions: the timing and location of both respondents and disasters. To be in the treatment group, (1) the respondent should reside in a county affected by a disaster, and (2) the interview should have taken place during the first *k* months after the event. In order to explore the temporal decay of the effects of the disasters on SWB, we allow for different values of *k*: two, four, six, eight, ten, and twelve months (Figure 3.1, panel A).

Panel A: Temporal assignment to treatment group



Panel B: Temporal and spatial assignment to treatment group

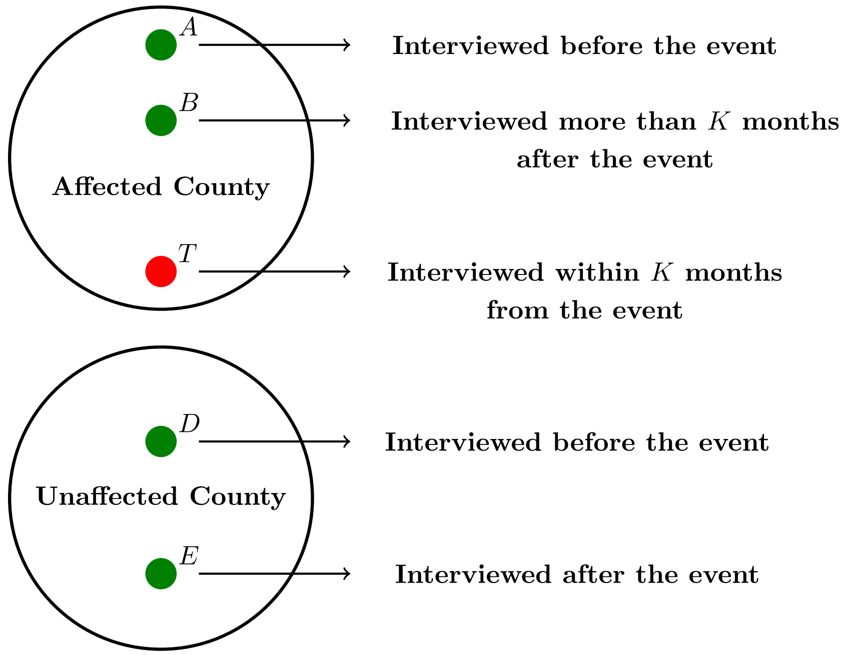


Figure 3.1: Temporal and spatial assignment to treatment and control groups

In panel B of Figure 3.1, point "T" denotes the treatment group consisting of those respondents who reside in a county affected by a disaster event and who are interviewed within *k* months of the event. In contrast, the control group includes those respondents who either reside in an unaffected county (D and E) or reside in an affected county but are interviewed before the event (A) or more than *k* months after the event (B).

To separate the effects of disasters from other confounding factors we utilize a multiple regression framework. We control for individual characteristics, unobserved time-invariant and unobserved time-variant effects by using socio-demographic variables, county fixed effects (FEs) and year dummies, respectively. County FEs control for geographical, climatic, or policy differences across counties that do not vary over the sample period. For example, they help control for whether the respondent lives close to the coast or in a county that participates in the National Flood Insurance Program (NFIP). As noted by Luechinger and Raschky (2009), risk-transfer mechanisms such as flood insurance can alleviate the effects of disasters on SWB. We investigate this in more detail in Section 5.1. We also control for possible correlation and heteroscedasticity among the residuals across counties by clustering the standard errors at the county level. We exclude counties with fewer than 50 respondents.[20]

Our benchmark model takes the following form:

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

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

Using the estimated coefficients from equation (1), in particular those for income and the disaster dummy, we can obtain the wellbeing effect of disaster and the willingness to pay to avoid being exposed to a disaster. The marginal rate of substitution of income for disaster place monetary value on the marginal change in number of disasters ($MRS = \left(\frac{\partial SWB}{\partial disaster} / \frac{\partial SWB}{\partial income}\right)$)

In a hypothetical setting, to keep her SWB constant, an individual would be willing to pay the

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

amount CS to avoid being exposed to a disaster $(d^0 = 1, d^1 = 0)$: $SWB(w, d^0) = SWB(w - CS, d^1)$. This amount is a compensating surplus:

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

As previously noted, the degree of exposure to a disaster can vary widely among individuals within the treatment group. For example, Cohen (2002) distinguishes between primary survivors, who have experienced maximum exposure to the traumatic event; secondary survivors, the grieving close relatives of primary victims; third level survivors who are the rescue and recovery personnel (e.g. medical and emergency staff, firefighters, police); fourth level victims or other people in the community involved in disaster reports and government personnel; and fifth-level victims who may experience states of distress or disturbance after seeing or hearing media reports. Our data do not allow us to distinguish between exposure categories, thus β_2 measures the *average* impact across the individuals residing in affected counties. Moreover, this parameter is not a laboratory-style estimate of the consequences of a disaster on SWB where all other factors are held constant, because it reflects individuals' actions to protect themselves from disasters.

3.3.1 Temporal decay of the impact of disasters

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

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

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

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

3.3.2 Exogeneity

The estimated treatment effects in equations (1) and (3) are consistent only when the assumption of exogeneity of natural disasters (i.e., treatment is randomized across individuals) holds; that is, when our proposed quasi-experimental identification strategy combining time and location generates a randomized sample. However, the use of observational data to estimate the treatment effect may be prone to selection bias. A concrete example of selection bias in this context is omitted variable bias that arises due to climate and geographical amenities (e.g. proximity to the coast) that impact both the location decisions of households and the probability of natural disaster occurrences. We minimize this concern by including county FEs in all specifications, which, as stated above, control for time invariant climatic and geographical characteristics.

Another way to address this problem that has become popular in microeconomic evaluation studies is the use of matching methods that aim to equate or “balance” the distribution of covariates in the treated and control groups. In our study, having thirty-seven individual level regressors, clustered within 2,209 counties across the U.S. raises the issue of a high dimensional vector X (“Curse of Dimensionality”) and limits the use of non-parametric matching methods to achieve balance between treated and control groups.[21] On the other hand, the enormously popular parametric method of propensity score matching described as a solution to the curse of dimensionality "[m]ay also accomplish the opposite of its intended goal and increase the imbalance, inefficiency, model dependence and bias" (King and Nielsen 2016).

Thus, the initial investigation of the data uses nearest neighbor matching with a logistic regression-based propensity score, where we impose a tolerance level of 0.25 on the maximum propensity score distance. First, the distance between the treatment unit and the closest control unit is estimated using propensity score, defined as the probability of receiving treatment conditional on the covariates. To prevent a noticeable reduction in the number of matched observations, we allow for replacement such that each control unit can be matched to more than one treated unit, and then each observation is assigned a weight that is used to estimate the average treatment effect. Figure 3.2, evaluating the balance on observables, illustrates no difference in the empirical distribution of propensity scores between the matched treated and control groups and the unmatched treated and control groups. This increases our confidence in the suitability of equations (1) and (3) to provide consistent estimates of the impact of disasters on individual SWB.

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

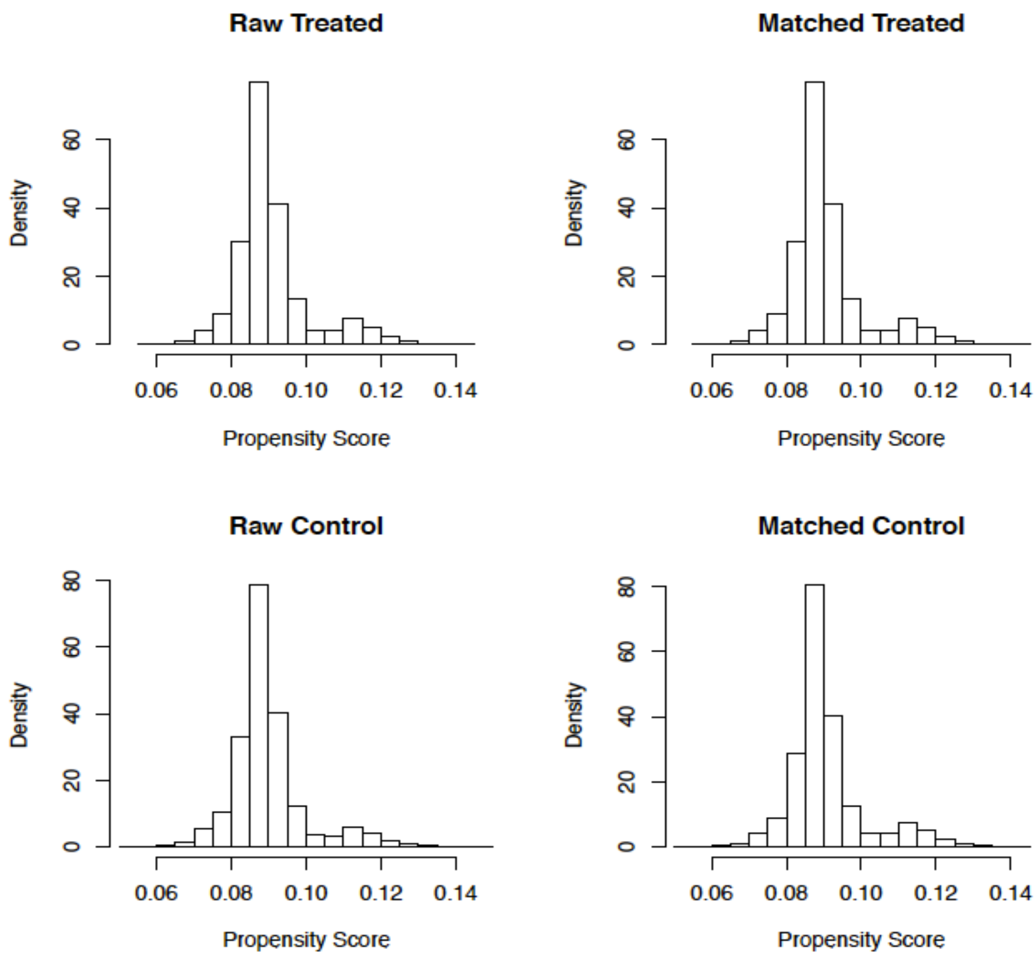


Figure 3.2: Distribution of propensity score for matched and unmatched treated and control groups

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

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

3.3.3 Disaster Type and Magnitude

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

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

where each disaster dummy (tropical cyclone, severe storm, flood, drought, wildfire and freeze) takes the value of one when the individual falls into the treatment group (for that particular disaster type) as previously defined. Table 3.1 panel B presents their descriptive statistics.

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

3.4 Results

In this section, we present the results for the different model specifications as defined in the previous section. All the models include the full set of socio-demographic variables, county FEs and year dummies. The coefficients on the socio-demographic controls, reported in Table 3.2, conform to expectations. Consistent with previous studies (Blanchflower and Oswald 2004, Oswald and Wu 2011), we find a U-shaped relationship between age and life satisfaction, with those 65 or older reporting the highest levels of life satisfaction. More years of schooling are associated with higher levels of life satisfaction in a non-linear fashion. Being separated is, as expected, negatively related to life satisfaction, and being married, widowed or cohabiting are positively related to life satisfaction, all relative to being single. Some of the most negative correlates of life satisfaction are unemployment (with no evidence of adaptation to this situation from those who are long-term unemployed) and being unable to work. Compared to those in poor health, those reporting other health categories fare much better, and the impact monotonically increases with better health. As expected, the coefficient on household income is positive and statistically significant.[22] All other races (except for Asian) report a slightly higher level of life satisfaction than whites. Males' life satisfaction is slightly lower than that of females.

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

Table 3.2: Effect of disaster on individual SWB across cumulative time windows

k	(1) 2 months	(2) 4 months	(3) 6 months	(4) 8 months	(5) 10 months	(6) 12 months	(7) 18 months
Disaster (dummy)	**-0.003***	**-0.004*****	**-0.004*****	**-0.003*****	**-0.002****	**-0.002***	**-0.001**
	(0.002)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Age (ref: 18-24)							
25 to 34	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
35 to 44	-0.085***	-0.085***	-0.085***	-0.085***	-0.085***	-0.085***	-0.085***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
45 to 54	-0.077***	-0.077***	-0.077***	-0.077***	-0.077***	-0.077***	-0.077***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
55 to 64	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
65 or older	0.077***	0.077***	0.077***	0.077***	0.077***	0.077***	0.077***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education	-0.039***	-0.039***	-0.039***	-0.039***	-0.039***	-0.039***	-0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Education^2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (Income)	0.108***	0.108***	0.108***	0.108***	0.108***	0.108***	0.108***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Marital Status (ref: Never married)							
Married	0.173***	0.173***	0.173***	0.173***	0.173***	0.173***	0.173***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Divorced	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Widowed	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Separated	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Cohabit	0.071***	0.071***	0.071***	0.071***	0.071***	0.071***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Race (ref: White)							
African American	0.059***	0.059***	0.059***	0.059***	0.059***	0.059***	0.059***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Asian	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Native Hawaiian/Pacific Islander	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)	0.034*** (0.010)
American Indian/Native Alaskan	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)	0.033*** (0.005)
Other	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

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

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

In the first row in Table 3.2 presents the coefficients for β_2 in equation (1) for seven cumulative time windows (k=2, 4, 6, 8, 10, 12 and 18 months). Turning to the first column, being treated by a natural disaster of any type in the two months before the interview, reduces the individual life satisfaction by 0.003 on the 4-point scale compared to the control group who are either being interviewed before the disaster, k months after the disaster, or live in another, unaffected region. The negative effect of being affected by a disaster is robust across all models, with k=6 months exhibiting the largest negative effect (-0.004) and best fit, as indicated by the BIC.

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

The *CS* to avoid exposure to a disaster event for those affected 6 months after the event is \$1,782. This estimated welfare loss, at 3.54% of average annual household income.[23] Since we cannot distinguish between those individuals directly and indirectly affected in the sample, the estimated *CS* reflects the average impact of a disaster; it may contain a combination of physical losses as well as psychological negative impacts across different levels of exposure.

Previous studies on the well-being impact of disasters (Luechinger and Raschky 2009, von

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[23] The estimated welfare loss: CS= -*exp*[10.827038 + (-0.0038907)/(0.1079818)(1-0)]+ 50364.313= 1782.383

Möllendorff and Hirschfeld 2016) choose 18 and 24 months as two additional time windows. We expand our window to 18 months for robustness and, as shown in Table 3.2, the estimated coefficient of the disaster variable is no longer statistically significant.[24] This suggests that, for our sample, the impact of disaster on SWB has fully decayed by then, and that failing in choosing the appropriate time window may lead to underestimating the disaster welfare loss.

Table 3.2 reports the results for a disaster dummy variable, but we also analyzed the robustness of the results to using the count of disasters in the previous *k* months in alternative specifications. Because most of the respondents are affected by at most one disaster during the previous 12 months, using the count of disasters instead of a dummy for occurrence of a disaster does not make a large difference in the results (not reported here but available upon request). The results for the disaster dummy variable and the number of disasters variable are similar, especially for shorter time horizons. As the time window broadens, and the number of disasters grows, the coefficient on the number of disasters variable is statistically more significant than for the disaster dummy, but we observe a similar pattern of decay in the magnitude of the effects with time.[25]

In equation (3) we explicitly test the hypothesis of temporal decay. As results in Table 3.3 show, having been affected by a disaster in the previous six months (independently of when it happened within the six-month period) has a comparable negative impact on SWB. The hypothesis of equality of effects of having been affected by a disaster within the last 2 months, last 2-4 months

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[24] Expanding the window to 18 months, requires including the billion-dollar disasters of year 2003.

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

and 4-6 months preceding the interview cannot be rejected. The coefficient becomes insignificant (t=0.65) for events that occur within 6 to 8 months preceding the interview and continues to drop in magnitude and significance thereafter. This time window is consistent with the results in Table 3.2 that 6 months is the optimal time window for investigating the impact of disasters. Compared to previous studies, this time frame is shorter than the 18 months considered by Luechinger and Raschky (2009) in their study of flooding in Europe, but longer than in the study by Kimball et al. (2006) in which the dip in happiness in the South-Central region of the U.S. was estimated to last only for two to three weeks after Hurricane Katrina.

Table 3.3: Effect of disaster on individual SWB for incremental time windows

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

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

All the regressions include individual characteristics and county FEs. This mitigates concerns about county-level omitted variables bias unless the omitted variables vary over time. For example, because of general economic decline in the U.S. during the late 2000s caused by the great recession, the negative association between disasters and SWB might be spurious if disasters are more frequent in more depressed areas. To capture the effect of macroeconomic decline during this time span that might be left out of county FE and year dummies, we repeated the regressions including the county level unemployment rate. The results (not reported here) did not change.

As an additional check on the consistence of our estimates, Figure 3.3 plots the results of the falsification test (equation 4). The coefficients of the "fake", lagged disaster variables are statistically insignificant. The estimated impact of true disasters, however, is the same as in Table 3.3. This corroborates that the main conclusions are not confounded by pre-existing differential trends between the SWB of affected and unaffected individuals.

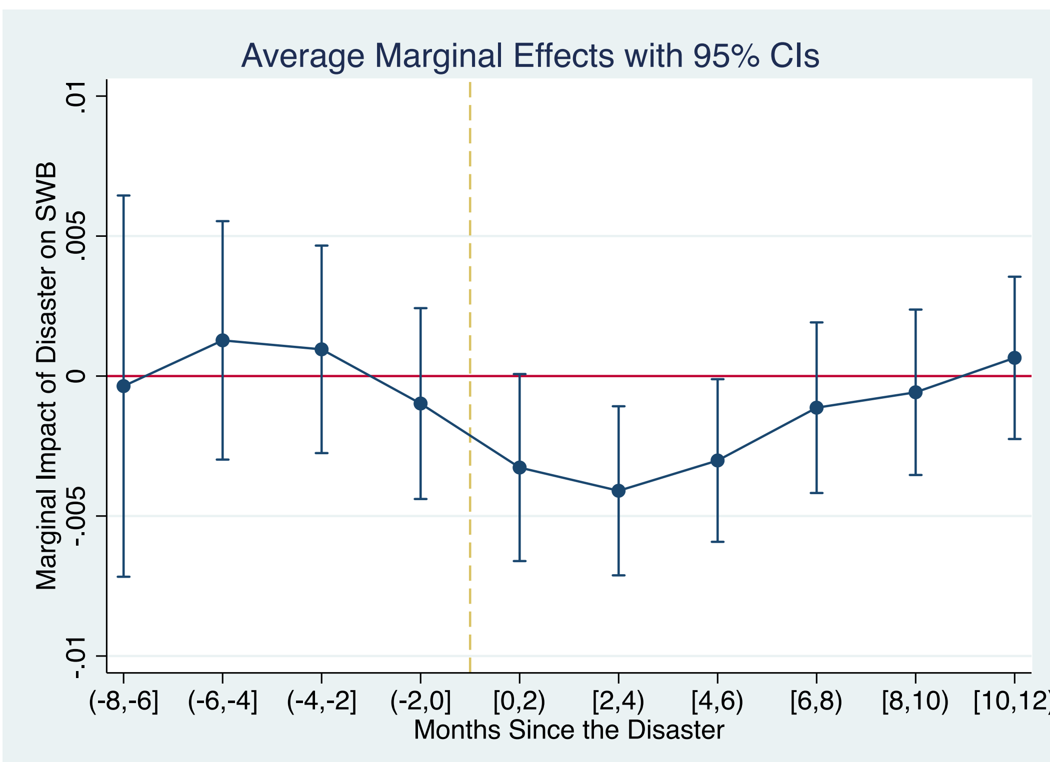

Figure 3.3: Falsification test on impact of disaster on SWB

Table 3.4 illustrates the impacts of different disaster types on SWB. Results are reported for the cumulative time windows of 6 and 8 months before the interview (in columns (1) and (2), respectively). Severe storms have a significant negative effect in both specifications. Although the ten tropical cyclones in the sample (especially a series of hurricanes in years 2004, 2005 and 2008) are among the most destructive weather disasters, no significant negative well-being effect is found within 6 and 8 months. Floods also exhibit insignificant coefficients in both columns. Droughts, on the other hand, show a negative, statistically significant (at a 10% level or better) effect on SWB and freeze is only significant in the 6 months specification. [26]

Table 3.4: Effect of different type of disaster on individual life satisfaction

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

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

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

When interpreting these results, one should keep in mind that when we disaggregate the total number of disasters by type, we are substantially reducing the size of the treatment group which makes it difficult to identify a statistically significant effect. This is particularly the case for the most infrequent and geographically concentrated disasters. While there were seventeen severe storms and tornados, there were fewer tropical cyclones (10), floods (4), wildfires (4), and freezes (2). Despite this, most *t*-statistics in the table are larger than 1. The sample includes only 5 droughts, but compared to other rapid onset disasters, droughts tend to be persistent. Three of them last for two seasons and two others affect a large population across U.S. states throughout the whole year.

The damage specification models by disaster type are presented in columns (3) and (4) of Table 3.4. Each disaster is weighted by its relative damage. The results continue to suggest that severe storms have the largest impact on SWB. Interestingly, although floods by themselves were marginally insignificant to explain life satisfaction in columns (1) and (2), they become marginally significant when weighted by their damages in the 8-month specification.

3.5 Additional exploratory analyses

3.5.1 Attenuating effects of insurance and governmental assistance programs

Risk transfer mechanisms such as natural-peril insurance and post-hoc disaster relief are designed to attenuate the negative financial implications of natural disasters. Using regional rates of insurance penetration in Germany, von Möllendorff and Hirschfeld (2016) show that insurance density can at least partly offset negative well-being effects of flood events. Similarly, the exploratory analysis of Luechinger and Raschky (2009) suggests that county participation in the NFIP fully compensates the effect of a flood event. Interestingly, our finding of a lack of significance of flood disasters in Table 3.4 is consistent with their observation.

In the U.S. flood insurance is provided by the NFIP to residents and small businesses in participating communities that adopt minimum floodplain management policies. In addition, NFIP communities can voluntarily participate in the Community Rating System (CRS) to receive premium discounts in exchange for floodplain management beyond the minimum requirements of NFIP (FEMA, 2017). All our regressions include county FEs, which control for (time-invariant) NFIP and CRS participation of affected counties. Thus, our estimates are an average of the effects of disasters for which the affected population is partially compensated by risk transfer mechanisms and of disaster events for which they are not.

The purchase of flood insurance is ultimately an individual decision.[27] Like in previous studies, however, data limitations prevent us from using individual level insurance data to net out the mitigation effect of insurance products. The best we can do to further investigate this effect and isolate the psychic costs of floods, is to estimate models that explicitly include two county-level flood insurance indicators: (1) NFIP participation, which takes value one when at least one community in the county participated in the NFIP before the flood occurred; and (2) CRS participation, which identifies if the county received discounted insurance premiums through CRS pre-flood.

Although severe storms and tropical cyclones are also associated with flood events in some locations, in this section we focus only on flood disasters because other extreme weather events under the severe storm and tropical cyclone headings (i.e., high wind, hail, etc.) are insured via homeowner insurance. However, the model includes indicator variables for other type of disasters

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

(severe storms and tropical cyclones) to net out the negative impact of other disasters. In the sample, four flood events occurred in years 2006, 2008 and two in 2010. Since the percentage of individuals who are interviewed less than six months after the disaster is 2.5 %, which is relatively low compared to the number of observations in the control group, we choose the eight months window with 3.3% affected individuals. No individual in our sample experiences more than one flood in this time span. Only 37% of individuals live in a county that provides indemnification against flood events in the form of NFIP at the time of disaster, and among them, only 37% are CRS participating communities.

Table 3.5 presents the estimated coefficients of the impact of floods on life satisfaction for U.S. counties with and without flood insurance. Compared with the results in Table 3.4, in this model the flood disaster dummy is negative and becomes statistically significant, which suggests that the impact of flood events on life satisfaction was suppressed by excluding the NFIP dummy variable. The estimated coefficient of the interaction term between the NFIP and flood dummies is positive and significant and of similar size as the flood dummy suggesting that flood insurance fully compensates the effect of flood events for individuals that reside in a NFIP participating county. Conforming to intuition, taking extra measures of floodplain management by participating in CRS programs also has a dampening effect that is statistically similar to that of NFIP participation (column (2)).

Table 3.5: Private and public risk transfer mechanism and flood disaster impact

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

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

From the coefficients in Table 3.5 we can also estimate the marginal impact of the flood at means, which is negative and statistically significant (it equals -0.006 and -0.005 for the NFIP and CRS participation models, respectively). From this we conclude that not all the damages of flood events are countervailed by insurance. Psychic cost of disasters, as noted earlier, also reduce the well-being of affected individuals (Luechinger and Raschky 2009). Insurance, however, helps; the costs to the average individual in non-participating communities are higher and statistically different (-0.010 and -0.006).

Governmental relief programs can also attenuate the impact of natural disasters, in some cases acting as substitutes for natural hazard insurance products (Kousky et al. 2018). In the U.S., the Disaster Relief and Emergency Assistance Act of 1988 provides disaster relief through the Disaster Relief Fund (DRF) after a federal disaster declaration. We consider two post-disaster governmental relief programs: the Public Assistance (PA) and Individual Assistance (IA) programs which are funded through DRF. PA is a community level assistance program funding "the repair, restoration, reconstruction or replacement of a public facility or infrastructure damaged or destroyed by a disaster" (FEMA 2018), while IA covers a broad range of post-disaster assistance including Mass Care and Emergency Assistance, Voluntary Agencies (VOLAGs), Individual and Households Program (IH), Small Business Administration (SBA), Disaster Unemployment Assistance (DUA), Crisis Counseling Services (CCP), and Disaster Legal Services (DLS).[28] In the sample, 26%, 56% and 51% of affected counties have received PA, IA, and IH assistance programs respectively. We investigate the effects of IA and IH programs separately to explore the importance of other programs under IA that may or may not be related to housing assistance and other needs assistance.[29] The interaction terms of governmental assistance programs in columns (3) to (5) of Table 3.5 show that IA and IHP both have a statistically significant attenuating impact on SWB. Although the PA interaction is not statistically significant, the overall marginal effect of

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[28] Retrieved from URL: https://emilms.fema.gov/IS403/lesson3/12010print.htm
[29] For more details see URL: https://www.fema.gov/media-library-data/1461689021638-cfcfd7f6c263635802fa7a76a19e00ea/FS001_What_is_Individual_Assistance_508.pdf.

disasters for recipients of this program (as well as for recipients of the other two programs) is not statistically different from zero.

3.5.2 Exploration of attenuating effects of general health insurance

Our data set does contain information on the purchase of health insurance. Although the purchasing decisions for natural peril insurance and health insurance are not comparable due to the different nature of the underlying risks (e.g. distributional differences in the probability of occurrence), and, in the case of flood insurance, the community participation requirement, we include health care access to try to net out the impact of health care costs following a disaster. Health insurance enrollment can bring peace of mind in the aftermath of catastrophic natural disasters and lessen their negative impact on SWB. A policy related question is to what extent can insurance-covered access to health services act as a coping mechanism to reduce the vulnerabilities of affected populations and work as a countervailing force to neutralize the negative impact of disasters?

In Table 3.6, we take a first stab at empirically answering this question. We re-estimate model 3 with an additional variable capturing health care access, a dummy that takes value one if the individual reports having access to health care including health insurance, prepaid plans such as Health Maintenance Organizations, or government plans such as Medicare.[30] Results show that the negative impact of a disaster within 2 months is almost fully mitigated for those who have access to health care coverage (captured by interaction between disaster variable and health care access dummy).

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

Table 3.6: Health care access and disaster impact

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

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

3.5.3. Impact of disasters on mental health

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

Protecting mental health after a disaster is often a central policy objective. For instance, under the Model State Emergency Health Powers Act (MSEHPA), out-of-state health care providers are allowed to practice as if they were licensed in the state when mental health services are in short-supply immediately after disasters (Rutkow et al. 2011). Other governmental systematic efforts include the Disaster Behavioral Health Information Series (DBHIS) by the Substance Abuse and Mental Health Services Administration (SAMHSA), which provides guidelines to improve the mental health resilience after natural disasters, and the Crisis Counseling Assistance and Training Program (CCP), which assist individuals and communities in recovering from the effects of natural disasters through the provision of community-based outreach and psycho-educational services (FEMA 2018).[31]

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

[31] Retrieved from URL: https://www.fema.gov/additional-assistance-disasters#0

Table 3.7 shows that individuals affected by a disaster are 1.02 times more likely to report 1 or more days of poor mental health than those who are not affected by the disaster. In terms of magnitude, this increase in likelihood of reporting poor mental health is equivalent to 70% of the increase in the likelihood of reporting poor mental health due to unemployment (odds ratio=1.46). Our estimates are community-level average impacts and lack the precision of psychological studies that seek to identify whether an individual is directly affected by disaster-related traumatic events or stressors or she has experienced PTSD. As noted by Cohen (2002), the negative impact of a disaster is different based on the time frames of "Impact Phase" (following the impact), "Short-run Phase" (weeks and months after the disaster) and "Long-run Phase". Our results suggest that the community-level average impact of disasters on mental health, stops being significant after 4 months, somewhere between the short run and long run phases.

Table 3.7: Disaster impacts on self-reported mental health

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

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

3.6 Discussion

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

In this study, we use a life satisfaction measure of SWB to estimate the effect of forty-two billion-dollar disasters on the welfare of U.S. residents between 2005 and 2010. The statistical investigation of results conforms to the intuition that extreme weather events and disasters negatively impact our well-being. We find that disasters reduce SWB (by approximately 0.004 on a four-point scale), that this effect decays over time and that it depends on the type and intensity of disasters. The compensation for preventing the disaster using SWB method is about $1782. To put this number in context the federal assistance provided by the Housing Assistance Program ranges from $5,000 to $25,000. As the time window between the event and the interview date increases so does the size of the treatment group which, by increasing the precision of the estimates, could lead to finding a significant effect of disasters for longer time horizons. This, however, should not necessarily be interpreted as a long-lasting effect of disasters. Indeed, we show that the negative effects of disasters decays after 6 months. These findings are important as they suggest a policy-relevant time frame to escalate the support systems to aid the community healing process. We also find that during the period of study, severe storms appear to be the disasters that most negatively affect SWB. Droughts also have a negative impact on life satisfaction and exhibit a more persistent effect.

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

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

CHAPTER 4

ECONOMIC VALUE OF MULTI-PERIL COASTAL HAZARD INSURANCE

4.1 Introduction

In the aftermath of Hurricanes Katrina and Rita, individuals and businesses in Louisiana, Mississippi, and Alabama protested against perceived inequities and obstacles in the settlement of property damage insurance claims. When insurance adjustors and damage experts assessed the properties damaged by these storms, they were faced with the difficult issue of allocating damages between wind (responsibility of private or state insurance) and flood (responsibility of federal government). Post-Katrina delays in damage assessments and extended litigation of insurance claims generated economic uncertainty and copious ill will among insurance holders and raised concerns about post-event judicial interpretations of the scope of insurance coverage. One insight that emerged from the wind vs. water claims dispute was the potential for expanding hazard coverage to permit policyholders to purchase multi-peril insurance. The idea of broadening hazard exposure for a catastrophe insurance program like the National Flood Insurance Program (NFIP) raises serious concerns among insurance experts due to actuarial difficulties in underwriting diverse catastrophes, practical problems of financial insolvency risk that currently exist for the NFIP, and existing private market insurance for other perils (King 2013).

Proponents of multi-peril insurance coverage, on the other hand, argue that such a product would eliminate coverage disputes for correlated hazards (e.g., flood, wind, and coastal erosion) while enhancing marketability and simultaneously allowing for reasonable amounts of cross-subsidization that could improve capital reserves (King 2013).

Currently, the NFIP offers indemnification from flood hazard in communities that agree to regulate development in floodplains. The mapping and regulatory standards of the NFIP, however, do not currently address erosion risk in coastal areas. Flooding and erosion risk are highly correlated along the waterfront; chronic erosion reduces beaches, dunes, and other sediments that maintain a buffer from waves, tides, and storm surge. Though not explicitly indemnifying property loss due to erosion, the NFIP pays an estimated $80 million per year in damages related to erosion (Heinz 2000). This, however, is just a fraction of projected erosion losses, a staggering $500 million per year over the next 60 years. As currently designed, NFIP policies cover erosion damage that occurs in conjunction with flooding, but not erosion losses that occur at other times (e.g. associated with strong waves). Community Rating System (CRS)[32] credit, nonetheless, is granted to coastal communities that include erosion hazard in their regulations, planning, public information, hazard disclosure, and flood warning programs, and this can result in discounted premiums for policy holders in these areas (FEMA 2016).

Since 1) flooding and erosion risk are correlated, 2) the NFIP currently indemnifies flood risk in coastal areas, and 3) there is considerable residual erosion risk for coastal property owners, we examine the potential for multi-peril coastal hazard insurance. We utilize existing survey data to analyze the potential demand for coastal hazard insurance that bundles indemnification of flood and erosion risks. Despite the availability of multi-peril insurance in countries like the UK, France and Germany, and the existence of multi-peril crop insurance in the US, little is known about the economic value of bundled natural hazard insurance. Catastrophe insurance programs like NFIP

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[32] Community Rating System (CRS) recognize communities for their additional efforts to (1) reduce flood damage to insurable property; (2) strengthen and support the insurance aspects of the NFIP; and (3) encourage a comprehensive approach to floodplain management (FEMA F-084/March 2011).

often have low market penetration, which limits the effectiveness of insurance and mitigation as risk management tools. While there are some potential explanations for low market penetration (Anderson 1974, Pasterick 1998, Wetmore et al. 2006[33]), individual difficulties in assessing risk are a common explanation. Multi-peril insurance contracts can address some of these difficulties by offering a broader range of coverage that could be more marketable (i.e. providing non-monetary utility such as "peace of mind" (Hogarth and Kunreuther 1995, Krantz and Kunreuther 2007).

A careful investigation of the demand of bundled insurance product requires study of various sub-groups with different individual and location characteristics. For instance, residents of hazard-prone areas value the option of multi-peril insurance that indemnify against potential disaster that could cause damage to their property; but they also refuse to pay an extra amount of money that reflect the damage faced by residents of other locations (Kunreuther, 2017). Bundling of hazard in a single policy will also lead to higher risk perception and increase the probability of buying insurance (Schade et al. 2012).

To the extent of our knowledge, ours is the first empirical study that combines revealed and stated preference data on different hazard insurance products to estimate welfare effects of bundling of insurance products. We utilize a unique dataset on households within approximately 1000 feet of the ocean on the southeast US coast (Atlantic and Gulf). The data includes information from the Federal Insurance Administration's policies-in-force database; field information on parcel-level risk factors collected by contractors for H.J. Heinz III Center for Science, Economics,

[33] Anderson 1974: inability of insurers to pool insureds with varying degree of exposure to flood losses because lower risks will not purchase coverage at a pooled rate. Wetmore et al. 2006: lack of insurer in the community and less vigorous enforcement of mandatory purchase requirement. Pasterick 1998: opting not to purchase flood insurance due to reliance on federal disaster assistance.

and Environment; and responses to a household survey questionnaire administered in 1998. The revealed preference data relates to flood insurance purchase and was previously utilized to analyze NFIP participation (binary outcome) (Kriesel and Landry 2004) and flood insurance coverage levels (censored, continuous outcome) (Landry and Jahan-Parvar 2011). Kriesel and Landry find generally greater flood insurance purchase in coastal areas and in areas with artificial erosion protection (shoreline armoring and/or beach replenishment). They find that distance from the shoreline and lower hurricane risk (as indicated by greater period between historical hurricane landfalls) decrease flood insurance purchase. Landry and Jahan-Parvar also find a positive correlation between erosion rates and flood insurance demand, suggesting that erosion risk may influence flood insurance purchase.

The stated preference data contain contingent valuation responses to offers of hypothetical insurance coverage for erosion damage and were previously analyzed by Keeler, Kriesel, and Landry (2003). They find a negative premium effect, positive income effect, and mixed results for erosion protection (negative for beach replenishment, but positive for shoreline armoring). We build on these studies by combining revealed and stated preference data, permitting correlation amongst purchase decisions, and examining the role of individual risk perceptions derived from survey responses. Our analysis contributes to the literature by investigating household risk perception, multi-peril insurance demand, and welfare effects of bundling hazard insurance. While our empirical focus is on flood and erosion insurance, our intent is to provide insight into the role of risk perceptions and bundling of insurance products for multiple perils on insurance purchase decisions and illustrate how combining individual risk perception of two perils increase the insurance demand through the deliberate thinking process.

The remainder of the chapter is organized as follows. Section 4.2 provides a review of the background literature on multi-peril insurance and effect of individual risk perceptions on insurance purchase decisions. Section 4.3 presents our conceptual model, and Section 4.4 introduces the study area and data sources. Section 4.5 describes the econometric model; Section 4.6 present estimation results and empirical findings, and section 4.7 concludes.

4.2 Background

4.2.1 National Flood Insurance Program and multi-peril insurance

Congress created the U.S. National Flood Insurance Program (NFIP) in 1968 to offer indemnification and guide management of flood hazard in participating communities. Broadly speaking, the NFIP aims to identify and map the nation's floodplains to make the public aware of flood hazards and to address the escalating cost of federal disaster assistance for flood damages. This national program attempts to partner with flood-prone communities to encourage adoption and enforcement of floodplain management measures in the form of guiding development and building practices. In return, households and businesses in participating communities can purchase insurance as protection against flood losses (King 2012).[34]

Since its inception, there have been numerous attempts to improve the performance of the NFIP, in particular to increase accuracy of risk rating, improve actuarial assessments, motivate participation by flood prone communities, and incentivize insurance uptake by individual households. For instance, the Flood Disaster Protection Act of 1973 expanded coverage to flood-related erosion losses, and in 1988 the Upton-Jones Amendment provided coverage for relocation or acquisition of properties that were in imminent danger of collapse due to encroaching shorelines.

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[34] More information on the history and structure of NFIP can be obtained from book written by Kunreuther and Roth (1998).

Citing limited effectiveness in incentivizing mitigation and a lack of premium basis to fund such coverage, the Upton-Jones provisions were later rescinded (Simmons 1988, Kunreuther and Roth 1989).

Since Hurricanes Katrina and Rita in 2005, the multi-peril insurance approach has been discussed as a way to address the NFIP's financial solvency problems and to deal with complications in attribution when various hazards contribute to property damages. Since then, attempts to amend the NFIP to cover multiple perils have been unsuccessful. For example, in 2009 Representative Gene Taylor of Mississippi introduced the Multiple Peril Insurance Act in the U.S. Congress, with the goal of adding wind hazard to flood insurance, but this proposal failed to gain attraction. Supply-side concerns surrounding multi-peril insurance include the difficulties in actuarial analysis and simulations that would be required to underwrite correlated catastrophic losses. Additional practical problems revolve around the current financial deficits in government catastrophe insurance programs (like NFIP) and how such programs would affect private insurance products for related perils (King 2013).

Nonetheless, there are potential benefits associated with bundling insurance products. First, multi-peril insurance could enhance efficiency in risk financing through greater pooling and diversification of risk (King 2013). Second, pooling many risks reduces the threats of depleting funds to pay out claims because it is less likely that a deluge of claims will arise out of a single catastrophic event, and paying out claims won't be deterred because there is no need to distinguish between the sources of damages (Majmudar 2009). Lastly, broad distribution of hazard coverage could result in better market penetration if households view multi-peril protection as a beneficial service that obviates the need for detailed assessment of individual-level risks, provides for overall piece of mind, and enhances the likelihood of quick and easy settlement of claims.

4.2.2 Risk perceptions and natural hazards

Like other common financial and investment decisions, demand for hazard insurance is influenced by risk perceptions and individual attitudes. Following standard convention, Bubeck et al. (2012) define *perceived risk* as combination of *perceived probability* and *perceived consequences* of an adverse event. A number of conceptual and theoretical frameworks exist for analyzing choice in risky contexts, but implementing these models in an empirical setting is difficult (Gilboa et al. 2008, Charness et al. 2013, Landry et al. 2017). Modeling choice under uncertainty is particularly problematic in the context of natural hazard insurance. Since probabilities are generally low, individuals tend to underestimate the likelihood of catastrophic natural events (Kunruther 1984, Schwarcz 2010, Browne et al. 2015), especially when there is no prior experience with a particular hazard (Kunreuther and Pauly 2004, Kunreuther and Pauly 2006, Siegrist and Gutscher 2006, 2008). This implies that subjective probabilities need to be assessed directly or revealed indirectly, typically via interviews or surveys (Morrison 1967, Schlaifer 1969, Hampton et al. 1973, Norris and Kramer 1990). Collection of primary data also permits analysis of risk perception in relation to socio-demographic factors, such as experience, family history, education, social factors (norms & position), and geographical location (Kogan and Wallach 1964, Harrison et al. 2007).

Risk perceptions (subjective probability) of natural hazards have been studied in recent years by using direct elicitation methods. In an experimental setting, Viscusi and Zeckhauser (2006) measure respondents' perception of 5th, 50th and 95th percentile expected temperature change in degrees Fahrenheit by asking respondents opinion about the upper bound, lower bound and best estimate of change in temperature. Baker et al. (2009) focus on a sample of Hurricane Katrina and Rita evacuees and examine the effect of individual's hurricane risk perception on hypothetical future location decisions. In their study, hurricane risk perception is measured with a graphical scroll bar, bounding hurricane risk between 0 and 100 percent.

Categorical measures of relative risk perception have been used in empirical analysis of wildfire risk mitigation (Martin et al. 2009) and hurricane evacuation (Lazo et al. 2010). Martin et al. (2009) use a composite measure of risk perception, constructed by combining information from five Likert-Scales questions that includes the assessment of both probability and consequences of impacts, to analyze wildfire risk mitigation decisions.[35] In a hypothetical setting, Botzen and van den Bergh (2012) apply Bayesian updating to elicit subjective probability of climate-induced flooding; they find a positive relationship between the insurance demand and risk perception. Petrolia et al. (2013) measure risk perceptions of hurricane return intervals and expected structural damages for a particular strength hurricane along the US Gulf Coast in their analysis of flood insurance demand; they find that individual with higher risk perception and prior experience of flood are more likely to participate in NFIP.

4.3 Conceptual framework

The decision to purchase insurance can be cast in the framework of utility maximization under uncertainty (Smith 1968). If we condition this decision upon subjective evaluation of risk, then it is equivalent to the concept of "Subjective Expected Utility" (Savage 1954). Consider a consumption prospect (x) that reflects current wealth (w) and the possibility of flood damage (d^f) and/or erosion damage (d^e) to a residential structure: $x_i = w_i - d_i^f - d_i^e$. Likelihoods of flood and erosion loss vary spatially according to trends in precipitation and sub-tropical storms, topography,

[35] Questions of risk perception and consequence of impacts: "to what extent do you feel concerned about the effects of wildfire", "how serious do you feel the negative consequences of wildfires are to you personally", "how vulnerable do you feel about the possibility of wildfire physically affecting you or your family", "how vulnerable do you feel about the possibility of wildfire affecting your property and/or possessions", and "how severe will the impact of a wildfire be where you live".

geomorphology, as well as physical attributes of structures at risk and surrounding public infrastructure. Subjective perceptions of risk also reflect individual factors, such as knowledge, experience, and beliefs.

Individual decisions on managing flood and erosion risk thus reflect subjective risk perceptions, utility levels associated with consumption prospects, availability and pricing of insurance and mitigation projects, and risk preferences. Packaging these elements in the subjective expected utility framework, we specify a decision model as (suppressing individual subscripts, *i*):

$$SEU(x) = \sum_{j \in f,e,fe} [p^j\,(h,z)U\big(w - d^j + n^j - \pi; \alpha\big)] + p^o(h,z)U(w - \pi; \alpha) \qquad (1)$$

where $p^j(h,z)$ is the subjective perception of event j = flood damage (f), erosion damage (e), flooding and erosion damage (fe), or no damage (o) (which depends upon localized physical conditions (h) and individual characteristic (z)); n^j is insurance cover for damage $j = f, e, fe$; π is the price of hazard insurance, and α indexes individual risk tolerance. Optimal choice of insurance cover thus represents a tradeoff between consumption in the no-loss state and the loss ($j = f, e, fe$) states. Demand for insurance n^j will be influenced by subjective perceptions of flood and erosion losses, conditional damages, wealth level, insurance premiums, and risk tolerance.

In this study, we focus on the role of empirically estimated subjective probability parameters ($\tilde{p}_i^j$) on individual decisions to purchase flood and erosion insurance coverage. Based on both theoretical (Kunreuther 1984) and empirical studies in the literature (Martin et al. 2009, Botzen and van den Bergh 2012, Petrolia et al. 2013), we expect that higher risk perceptions increase insurance demand. We utilize first-stage regressions that map indicators of latent risk perceptions into the unit interval, while permitting correlation among perception of flood and erosion risk. While not a structural model, utilizing survey data to estimate subjective risk perceptions improves the model and incorporates structural parameters in estimation.

Unfortunately, information on other structural parameters in equation (1), such as expected losses and indictors of risk aversion, are not available in this study.

We posit individual risk perceptions as a function of physical risk factors—flood zone and shoreline erosion rate—and an indicator of hazard mitigation efforts (presence of shoreline stabilization structures such as seawalls, rip-rap, groin, break water or utilization of beach replenishment). Households located in the Special Flood Hazard Area (SFHA, also known as the 100-year floodplain) face federal flood insurance requirements for the majority of mortgage contracts and are exposed to flood-risk disclosure provisions in some areas. Perceptions of risk can also be influenced by public infrastructure projects that are designed to mitigate hazards (Botzen et al. 2009, Bubeck et al. 2012, Peacock 2003). The influence, however, is ambiguous, as mitigation projects can convey a sense of security (reducing risk perception) or heighten saliency of vulnerability (increasing risk perception). Individual factors affecting risk perception include prior experience with hazards and demographic factors like age and education. Previous research has found that prior personal experience with natural hazard losses increase risk perception (Browne and Hoyt 2000, Lindell and Perry 2004, Peacock et al. 2005). This pattern is consistent with the Bayesian learning model of Viscusi (1991) in which individuals may exhibit overly optimistic expectations of disaster loss prior to experiencing an event (Palm et al. 1990, Kunreuther et al. 1987). Experience can foster learning, which may influence risk perceptions. For instance, Martin et al. (2009) found relatively high correlation between the risk perception and subjective knowledge about wildfires. Other individual characteristic such as age and education can also play a role in risk perception and evaluation. In a general context, Savage (1993) illustrates that for four common hazards (aviation accidents, fires in the home, automobile accidents, and stomach cancer) younger people have significantly higher "dread" of hazards than older people.

4.4 Study area and data

The dataset in this study includes information from Federal Insurance Administration's policies-in-force database; parcel-level field data collected information by H.J. Heinz III Center for Science, Economics, and Environment under the direction of FEMA; and household-level survey questionnaire responses collected in 1998.[36] Combining these information sources, we make use of both revealed and stated preference data on insurance purchase decisions in coastal counties, seeking insight into economic value of multi-peril insurance products[37]. The coastal counties (presented in Figure 4.1) are located in North Carolina (Brunswick and Dare), South Carolina (Georgetown), Georgia (Glynn), Florida (Brevard and Lee), Texas (Brazoria and Galveston) and Delaware (Sussex), with North Carolina, Texas, and Florida providing the bulk of survey respondents (41, 29, and 11 percent, respectively)[38].

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[36] As of March 1998, 18,760 communities out of 21,000 flood-prone communities, had joined the NFIP with approximately 4 million policies-in-force (Pasterick, 1998)

[37] All counties in this study are participating in the NFIP.

[38] Based on the study by Dixon et al. (2006) nearly 60 percent of single-family homes (SFHs) in the SFHAs nationwide are in the south, and market penetration rate of SFHs is considerably higher in South and West of U.S (approximately 60 percent). Besides, under plausible assumptions, the compliance rate with the mandatory purchase requirement in the south is 80 to 90 percent. This gives us confident that results of this study would hold for the NFIP eligible property owners that may experience erosion.

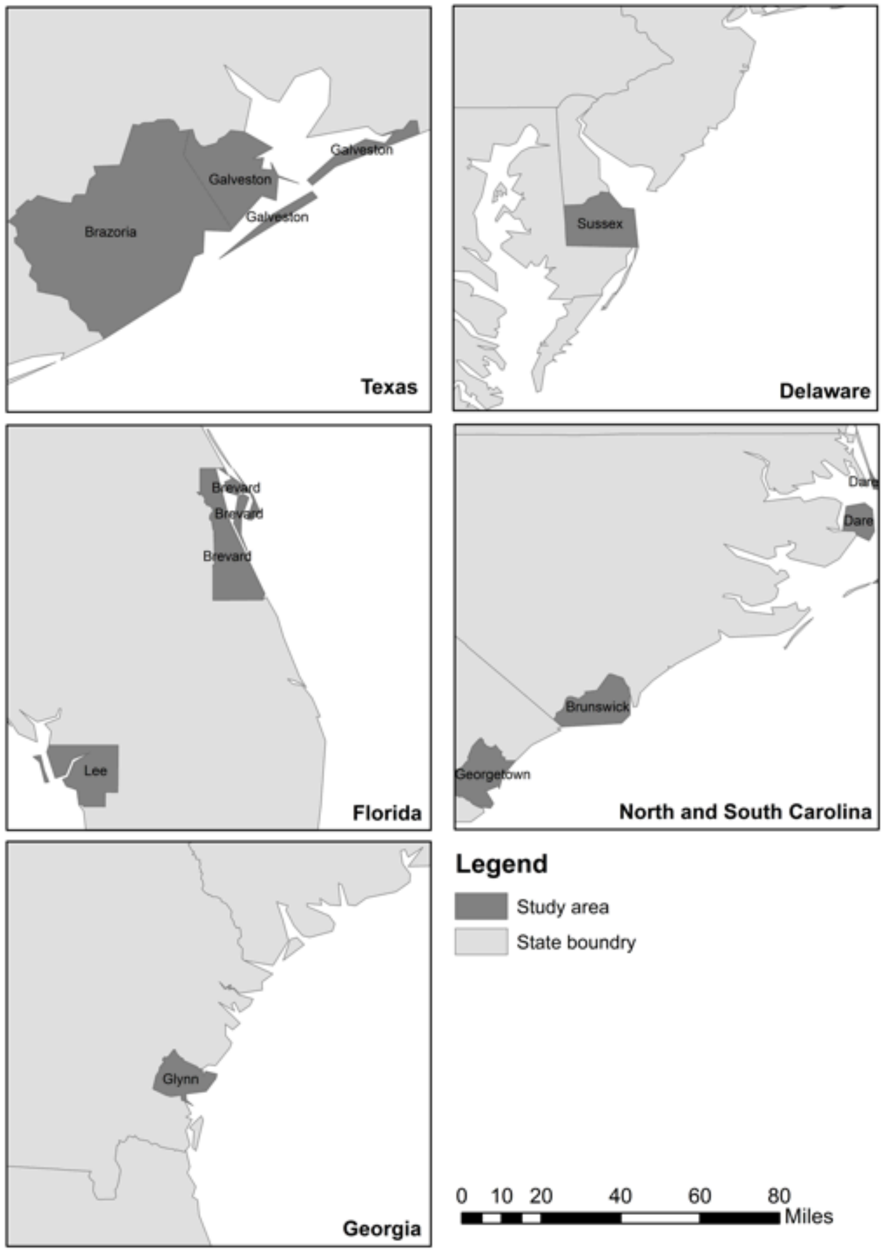

Figure 4.1: Study area

Galveston and Brazoria counties in Texas have the highest number of residents in high flood risk areas (V-Zone), while most of residents in Lee and Brevard Counties locate in moderate (A-Zone) and low risk areas (B/X/C Zone). It should be noted that to ensure adequate coverage on the oceanfront, which was focus an important aspect of the original study, stratified sampling was used. Thus, summary statistics and econometric estimation must employ sampling weights. In the remainder of this section, variables from various data sources are introduced. Table 4.1 presents the description of variables and source of data in our analysis.

Table 4.1: List of variables

Variable	Source	Description
Location variables		
Dare NC, Brunswick NC, Glynn GA, Georgetown SC, Brevard FL, Lee FL, Galveston TX, Brazoria TX, Sussex DE	Survey	Indicator of the county
X/B/C-Zone	Heinz Center	SFHA- Minimal risk area
V-Zone	Heinz Center	SFHA-higher risk area
A-Zone	Heinz Center	SFHA-Moderate risk area
Elevation (feet)	Field survey	Structure elevation
Distance from shore (100 feet)	Field survey	Structure distance from the shoreline in feet
Oceanfront	Field survey	Dummy: 1= building is oceanfront
Erosion or accretion (feet/year)	Heinz Center	Erosion or accretion rate
Flood and erosion related variables		
NFIP participant	Survey	Dummy: 1=participating in NFIP
Erosion willingness to pay	Survey	Willing to pay for addition of erosion coverage to NFIP, Dummy: 1=yes response to the erosion bid
Flood coverage premium (annual per $100 covered assessed asset value)	Estimated using Federal Insurance Administration's policies-in-force database	Assuming full coverage, this price is derived by dividing the full insurance coverage by the asset value
Erosion coverage premium (annual per $100 covered assessed asset value)	Survey	Assuming full coverage, this price is derived by dividing the erosion insurance bid by the asset value
Mandatory flood insurance	Survey	Dummy: 1= If individual is required to participate in NFIP
Assessed asset value ($10000)	Estimated in Jahan-parvar and Landry 2009	Estimated using Hedonic Price Regression Model
Flood nominal risk perception	Survey	Binary choice variable: 1=

		individual would buy the insurance regardless of any obligation from NFIP (flood risk is high), 0= would not buy the insurance (flood risk is low)
Erosion nominal risk perception	Survey	Binary choice variable: 1= individual expects property value loss because of erosion (erosion risk is high), 0= individual does not consider erosion as a serious problem (erosion risk is low)
Filed insurance claim	Survey	Dummy: 1= filed insurance claim
Erosion mitigation measure	Survey	Dummy: 1= engaging in measures that prevent erosion including seawall, rip-rap, groin, jetty, break water, sand nourishment, dune fences, dune grasses, raised walkways
Socio-demographic variables		
Graduate school degree	Survey	Dummy: 1= attend graduate school
College degree	Survey	Dummy: 1= attend college
Age	Survey	Respondent age
Income	Survey	Annual Household income

4.4.1 Revealed preference information on flood insurance purchase

Revealed preference information on flood insurance purchase is available from both the Federal Insurance Administration's policies-in-force database and the household survey questionnaire. The policies-in-force database contains accurate information on coverage levels, deductibles, and other aspects of NFIP insurance contracts. Table 4.2 presents the descriptive statistics of variables used in our analysis.

The field data permit accurate assessment of parcel-level risk factors and flood insurance prices (which depend upon elevation above base flood, among other things). Information on structure elevation, ocean frontage, distance from shoreline, flood zone (V-Zone, A-Zone, and B/C/X-Zone) and erosion and accretion rates are provided from Heinz Center (2000) field survey.

Overall, 52% of the properties are located in the V-zone (100-year flood zone), which is among the "Special Flood Hazard Areas" (SFHA), but with additional risk of high-velocity waves due to storm surge. Another 33% of the properties are located in A-zone, which is the standard SFHA or 100-year flood zone. Other properties are located in moderate or minimal flood risk area referred as B/C/X zone, which is the reference category in our estimation. [39] The vertical and horizontal distances in this study ranges from 10 feet below to 29 feet above the sea level, and 0 to 1700 feet from shoreline, respectively. Thirty-five percent of properties are classified as oceanfront properties, and 94% are located along an eroding shoreline (with average erosion rate of 3.5 feet per year). The small minority of properties is located in accreting areas, with average accretion rate of 1.4 feet per year. The erosion variable in our analysis takes negative values for the accretion and positive values for erosion.

Full coverage premium for each property is estimated using NFIP rate tables and detailed property characteristics, such as year of construction relative to release of Flood Insurance Rate Maps (FIRM), being located in the Special Flood Hazard Area (SFHA), structure value,[40] and physical characteristics, like having a basement, elevation on piles, etc.[41] The average estimated full coverage premium is $1,050 hundred dollars. Full coverage premium is divided by the structure value so that normalized flood insurance price is expressed in units of coverage and also be comparable with the erosion coverage premium that will be explained later. The flood insurance coverage premium ranges from $0.07 to $4.20 per $100 covered assessed asset value.

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[39] To ensure adequate coverage on the oceanfront and reporting representative statistics, stratified sampling and weights are used.

[40] We used the assessed value of structure estimated by hedonic regression model from Landry and Jahan-Parvar (2011).

[41] Detailed explanation on the underlying assumptions of estimating full coverage premium is available in Landry and Jahan-Parvar and can be provided upon request (2011).

Table 4.2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Location variables				
Dare, North Carolina	0.31	0.46	0.00	1.00
Brunswick, North Carolina	0.13	0.33	0.00	1.00
Glynn, Georgia	0.01	0.09	0.00	1.00
Georgetown, South Carolina	0.05	0.22	0.00	1.00
Brevard, Florida	0.12	0.32	0.00	1.00
Lee, Florida	0.05	0.23	0.00	1.00
Galveston, Texas	0.26	0.44	0.00	1.00
Brazoria, Texas	0.04	0.20	0.00	1.00
Sussex, Delaware	0.08	0.28	0.00	1.00
B/C/X Zone	0.15	0.36	0.00	1.00
V-Zone	0.52	0.50	0.00	1.00
A-Zone	0.33	0.47	0.00	1.00
Elevation (feet)	3.60	6.50	-9.97	28.71
Distance from shore (100 feet)	3.78	2.58	0.00	17.00
Oceanfront	0.35	0.48	0.00	1.00
Erosion or accretion	2.76	3.54	-22.99	18.27
Flood and erosion related variables				
NFIP participant	0.59	0.50	0.00	1.00
Erosion willingness to pay	0.26	0.44	0.00	1.00
Flood coverage premium	0.84	0.75	0.07	4.19
Erosion coverage premium	9.41	16.00	0.00	104.51
Assessed asset value	1,718.11	2,034.71	201.23	23,619.3
Mandatory flood insurance	0.13	0.33	0.00	1.00
Flood nominal risk perception	0.34	0.47	0.00	1.00
Erosion nominal risk perception	0.53	0.50	0.00	1.00
Filed insurance claim	0.10	0.30	0.00	1.00
Erosion mitigation measure	0.65	0.48	0.00	1.00
Socio-demographic variables				
Graduate school degree	0.37	0.48	0.00	1.00
College degree	0.45	0.50	0.00	1.00
Age	61	11	25	92
Income	156,204	162,954	15,000	527,805

4.4.2 Survey data and stated preference information on erosion insurance purchase

The survey data collected through mail questionnaire provides detailed information on flood and erosion risk perceptions; previous experience with flood damage or filing of flood insurance claims; socio-demographic characteristics including age, education, and income; and a stated preference question inquiring about individual willingness to purchase additional insurance for erosion damage. The stated preference scenario was described as follows:

> *Suppose that the National Flood Insurance Program were expanded to cover erosion damages, regardless of whether a flood had occurred. To avoid being subsidized by tax dollars, the Program would have to charge policyholders more for this expanded coverage.*
>
> *Suppose that this expanded erosion damage coverage was offered to you for an additional $_____________ per year above what you now pay. Would you purchase this coverage?*

Offer prices were expressed as an annual payment, varying randomly in 30 increments from $25 to $24,000, and were defined as an additional payment to current premium (which is zero for NFIP non-participants). Following procedures with flood insurance price, the offer price for erosion coverage is divided by the assessed structure value so that erosion insurance price is expressed in units of asset value covered; proposed erosion insurance coverage premium ranges from approximately $0 to $104.5 per $100 covered assessed asset value (Table 4.2). 59% of households in our sample are NFIP participants, and 31% of them are willing to pay for the addition of erosion coverage to the NFIP. 13% of NFIP non-participants elect to pay additional premium for the optional erosion coverage. 15% of respondents perceive that they are required to purchase the flood insurance provided by NFIP, and our data suggest that 93% comply.

Regarding our interest in investigating the impact of risk perception on insurance purchase decision, two questions in the survey data provide information on individuals' risk perception for flood and erosion damages that enable us to estimate a model of individual "joint flood-erosion risk perceptions." In the flood section of the survey questionnaire, individuals provide a binary respond to the question, "would you have purchased coastal property regardless of whether flood insurance were available?" We interpret no response as reflecting high flood risk perception and yes response as reflecting low flood risk perception. For individual perceptions of erosion risk, we utilize responses to the question, "How likely do you expect it is that erosion occurring over the 30 next year will significantly reduce the price for which your property could be resold by you or your heirs?" Respondents that indicated no chance or unlikely are not worried about the erosion risk and they are identified as having low erosion risk perception, whereas those answering likely or highly likely have higher tendency to worry about the erosion damage in the future and they are identified as having high erosion risk perception. For simplicity, we refer to these two variables as nominal risk perception that capture the general tendency to worry about flood and erosion hazards and use them to determine the estimated parameter of joint flood-erosion risk perception, flood risk perception and erosion risk perception.

We use indicator of filing a flood insurance claim, as the proxy for the personal prior experience of the natural disaster. Among all respondents, 10% state that they have experienced flood damage and filed insurance claim. To capture impact of erosion mitigation measure at community level on risk perception we use an indicator variable that takes value one when any of erosion mitigation measure (*sea wall, rip-rap, groin/jetty, break water, sand nourishment, dune fences/dune grasses, raised walkways, others*) has been attempted during the time that respondent own the property. Sixty percent of respondents claim that at least one of the above erosion mitigation measures has been used in their community to protect against erosion.

4.5 Econometric model

In this study, we utilize a two-step regression analysis. First, we estimate the joint risk perception of individuals for flood and erosion using bivariate Probit, and then we estimate flood and erosion insurance demand conditional on the results of the first step estimation and determine the marginal effects of relevant covariates (e.g., insurance price, risk perception) and mean willingness to pay for the multi-peril insurance product.

4.5.1 First step: Joint flood-erosion risk perception

Empirical approach for solving subjective expected utility maximization problem is to set up a reduced form specification for the Marshallian-type demand function with assuming linear approximation of subjective expected utility.

We incorporate flood nominal risk perception (R_{fl}) and erosion nominal risk perception (R_{er}) in a bivariate probit model, to utilize all the available information that affects individual risk assessment, and generate a subjective risk measure for multi-peril coastal hazard using non-nested seemingly unrelated regressions.

$$R_{er}^{*} = X_1\beta_1 + \varepsilon_1, \quad R_{er} = 1 \; if \; R_{er}^{*} > 0 \,, 0 \; otherwise \tag{2}$$

$$R_{fl}^{*} = X_2\beta_2 + \varepsilon_2, \quad R_{fl} = 1 \; if \; R_{fl}^{*} > 0 \,, 0 \; otherwise \tag{3}$$

$$[\varepsilon_1 \quad \varepsilon_2 | \, X_1 \,, X_2] \sim N[(0,0), (1,1), \rho], \tag{4}$$

where R_{fl}^{*} and R_{er}^{*} are latent variable representations for individual risk perception of flood and erosion; R_{fl} and R_{er} equal one indicating high flood and erosion risk perception, respectively. Evaluating the bivariate normal CDF (Equations (5)) gives us conditional estimates of individuals' subjective probability of flood and erosion loss:

$$\pi_{11}(\hat{\theta}) = \Pr(R_{fl} = 1, R_{er} = 1 | \, X_1 \,, X_2 \,), \tag{5}$$

where $\theta = (\beta_1 \quad \beta_2 \quad \rho)$ is vector of regression and correlation coefficients for flooding and erosion risk perception equations.

In a general setting, we assume normality and utilized the Probit model in order to estimate the reduced form; therefore, the perceived predicted probability of flood and erosion for each individual is the evaluated joint probability distribution obtained from bivariate estimation of flood and erosion nominal risk perception, conditional on vector of individual characteristic variables and location determinants in X_1 and X_2. Vector X_1 includes age, level of education, having filed an insurance claim, distance to shoreline, indicator for property located in the 100-year flood zone-SFHA (V-zone and A-zone) and X_2 includes all the above and include taking mitigation measures for erosion instead of variable denoting experience with a flood.

With a significant correlation coefficient between flood and erosion nominal risk perception equations, the natural conditions for well-behaved probability distribution and the underlying assumption of normality provide reasonable conditions for identification. Fitting latent risk perception response data with a bivariate normal cumulative distribution function confines all the conditional probabilities between 0 and 1 and guarantees the sum of the probabilities for occurrence of each mutually exclusive event (i.e. no loss; flood loss; erosion loss; erosion & flood loss) equals one (Anderson et al. 1977) – desirable conditions for a subjective probability distribution function. These natural conditions for well-behaved probability distribution and the assumption of normality provide reasonable conditions for identification when it is difficult to find instrumental variables that would permit clear identification of the subjective probability function. Furthermore, nominal risk perception variables that capture the level of worry toward the hazard loss reflect an emotional state that leads to ambiguity, comparing to cognitive assessment in the subjective risk perception. Based on previous studies ambiguity imposes a larger positive impact on the insurance decision (Schade et al. 2012) and lead to higher WTP. Schade et al. (2012) argue that worry and risk perception are independent indicators of individual perception toward risk and they both contribute to a higher WTP for insurance products. Therefore, the benefit of estimating risk perception parameter utilizing two indicators of worry is that by updating and correcting individual worry based on individual and location determinants of subjective probability, we obtain a suitable proxy for unobserved subjective probability in this study. We assume that estimated parameter of risk perception satisfies the proxy variable assumptions: in the linear projection, the unobserved subjective probability is $SP = \gamma_0 + \gamma_1 \pi_{11}(\hat{\theta}) + r$. The measurement error (r) with zero mean, uncorrelated with SP, and uncorrelated with other factors appearing in X_1 and X_2, leads to a consistent estimate of risk perception and insurance premium variables that are key variables in this study. Using the parametric bootstrap procedure in estimating models (Efron and Tibshirani 1986), we acknowledge and offer a remedy for possible violations of these assumptions that cause the underestimation of the impact of risk perception and inconsistent estimation of insurance premium, among other variables in the model.

To investigate the robustness of our analysis, we investigate two alternative models. First, instead of using X, we reduce the dimensionality of vector X by using the Multiple Correspondence Analysis (MCA) and substitute X with $F(X)$ in equations (2) to (5). Using MCA method, we obtain a linear combination of X and control for the common trends of variation behind influential regressors. This approach avoids loss of degree of freedom in the first step regression, and deal with the multicollinearity problem between estimated risk perception parameter and vector X in the second stage regression. However, the estimated scores from the MCA analyses on indicator matrix of categorical variables does not carry the characteristic of probability and take positive and negative values greater than and less than one. Second, we also check the robustness of explanatory power of joint flood-erosion risk perception by estimating the marginal probability of flood and erosion separately, and include them in each regression based on the relevance:

$$\pi_{\mathrm{fl}}(\hat{\theta}) = \Pr(R_{fl} = 1 \mid \mathrm{X}) \qquad (6)$$

$$\pi_{\mathrm{er}}(\hat{\theta}) = \Pr(R_{er} = 1 \mid \mathrm{X})$$

This exploratory analysis has the advantage of looking at different gradients of risk perception of four possible outcomes (i.e., state of occurrence of both flood and erosion, state of flood and no erosion, state of erosion and no flood, and no flood and erosion). Incorporating different estimation of individual risk perceptions in the estimation of the multi-peril insurance allows us to explore the effect of offering multi-peril insurance product in forming individual risk perception.

4.5.2 Second step: Multi-peril hazard insurance demand

We allow for the interdependence of flood and erosion insurance demand by modeling the binary responses simultaneously in a bivariate Probit framework and define $y_{1i} = 1$ if a household participates in the NFIP (equivalent to "yes" response to flood insurance bid price per \$100 coverage, and zero otherwise) and $y_{2i} = 1$ if the individual response to the erosion stated preference scenario is affirmative (indicating WTP for the offered premium per \$100 coverage, and zero otherwise). Using bivariate Probit likelihood function, defining $d_{1i} = 2y_{1i} - 1$ and $d_{2i} = 2y_{2i} - 1$, the i^{th} observation contribution to the likelihood function is:

$$L_i(\mu_i | d_{1i}, d_{2i}) = \Phi_{\varepsilon_1,\varepsilon_2}\left(d_{1i}\left(\frac{bid_{fl,i} - \mu_{1i}}{\sigma_1}\right), d_{2i}\left(\frac{bid_{er,i} - \mu_{2i}}{\sigma_2}\right), d_{1i}d_{2i}\rho\right) \qquad (7)$$

where $[\varepsilon_1 \quad \varepsilon_2 | \mathrm{X}_1, \mathrm{X}_2] \sim \mathrm{N}[(0,0),(1,1),\rho]$ in the stochastic part of utility and μ_{ji} is means for the response that depends on the individual covariates ($\mu_{ji} = \mathrm{X}_{ji}\beta_j$) (Haab and McConnell 2002). X_{ji} are determinants of insurance demand function as it is introduced in equation (1) and

(4) including the estimated joint risk perception parameter (and marginal flood and erosion risk perception in alternative scenarios) in the first-step regression. The use of an estimation of initial regression equation (i.e. inclusion of an imputed variable), however, introduces a generated regressor problem (Wooldridge 2002), which complicates inference. To tackle this issue, we use a parametric bootstrap procedure introduced by Efron and Tibshirani (1986).

The mean willingness to pay for flood and erosion insurance is estimated using the parameters of each equation; If $WTP_{ji} = \mu_{ji} + \varepsilon_{ji}$, WTP_{ji} represents the ith respondent's willingness to pay and j=1,2 represents answer to participation question for flood and erosion insurance. The estimated mean WTP facilitates analysis of welfare gain/loss from bundling flood and erosion insurance products. The initial assessment of distribution of the erosion purchase price illustrates that assuming normal distribution for the error term will lead to mean willingness to pay outside the realm of feasible values (negative mean WTP). Therefore, we estimate the exponential WTP ($WTP_{ji} = e^{\mu_{ji}+\varepsilon_{ji}}$) and report the median WTP for insurance products.

To find the population of interest that has higher willingness to pay for the proposed multi-peril insurance, we investigate two subsamples in this study. First, we hypothesize that residents of oceanfront properties are more likely to have willingness to pay for the bundled insurance product and experience larger welfare gain if the erosion insurance market introduced to NFIP. As discussed before, bundled insurance product can improve risk pooling for the insurer, if erosion insurance seems appealing to residents of erosion-prone areas who are not required to purchase flood insurance. Therefore, second subsample of interest investigate portion of households who are not required to participate in NFIP.

4.6 Results

Table 4.3 presents the result of first step regression to identify influential regressors to estimates the individual joint risk perception parameters. Distance from the shoreline decreases the probability of stating high flood risk perception. For every 100 feet from the shoreline the probability of being concern about the flood decreases by 1.7% for the flood and 2% for the erosion. This being said, while proximity to shoreline plays a significant role in forming risk perception, it generates more uncertainty toward erosion risk compared to flood risk. Consistent with previous studies, prior flood experience leads to higher risk perception (marginal effect of 9%), and erosion mitigating measures undertaken by the local government in the community increases prior knowledge about the erosion and increases erosion risk perception by 13%. Attending college and graduate school compared to high school can lead to higher level of nominal risk perception for the flood, but not erosion. The likelihood ratio test of ρ for correlation between flood and erosion nominal risk perception equations that are presented in column (1) and (2) is significant at 10% (chi2(1) = 3.52932, Prob > chi2 = 0.0603).

Table 4.3: First step regression; joint flood-erosion risk perception

	(1) Flood nominal risk perception	(2) Erosion nominal risk perception
Distance from shoreline	-0.052**	-0.063**
	(0.021)	(0.025)
100-year flood zone	0.197	0.463
	(0.178)	(0.338)
Flood insurance claim	0.259***	
	(0.039)	
Erosion mitigating measure		0.344**
		(0.167)
Graduate school	0.446**	-0.045
	(0.213)	(0.163)
College	0.207	0.035
	(0.212)	(0.163)
Age	-0.021***	-0.006
	(0.004)	(0.003)

Constant	0.612*	0.039
	(0.345)	(0.300)
Observations	1207	1196

Notes: Clustered standard errors at county level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 4.2 shows the cumulative density functions of joint risk perception parameter. From estimated CDFs of joint risk perception (equation 5) and flood and erosion marginal risk perceptions (equation 6), approximately 50% of respondents have a perception lower than 0.23, 0.37, and 0.6, respectively. The first order stochastic dominance of food risk perception by erosion risk perception denotes the importance of coupling the risk perception of hazards in the estimation of subjective risk perception when facing correlated hazards.

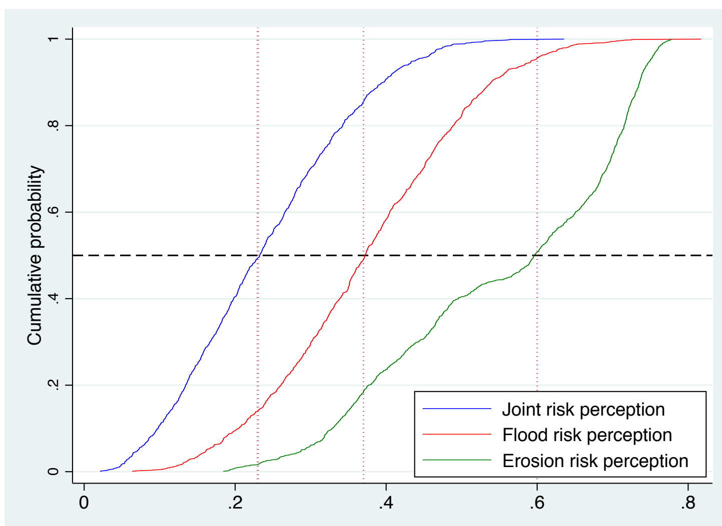

Figure 4.2: Cumulative density function of joint and marginal risk perception

Utilizing the MCA method that analyzes the observations on more than two categorical variables, we reduce the dimensionality of design matrix X to generate an alternative proxy for the unobserved risk perception variable.[42] Two main dimensions of the data (65%) are mainly

[42] For obtaining optimum total inertia and a better presentation of the MCA analysis we convert two continuous variables of distance from the shoreline and age into categorical variables based on quartiles and used the most

explained by the association between location determinants such as being located in SFHA, as well as the binary variable of experiencing a flood and filing an insurance claim (Figure 4.3). The pattern in the MCA plot conveys detailed information on how location characteristics (e.g., SFHA and distance from shoreline) and individual characteristics (e.g., age, education, erosion measure, and flood claim) are clustered in the dataset. This also illustrates the association between categories of influential factors such as living in high hazard areas (i.e., vzone and azone) and flood experience.

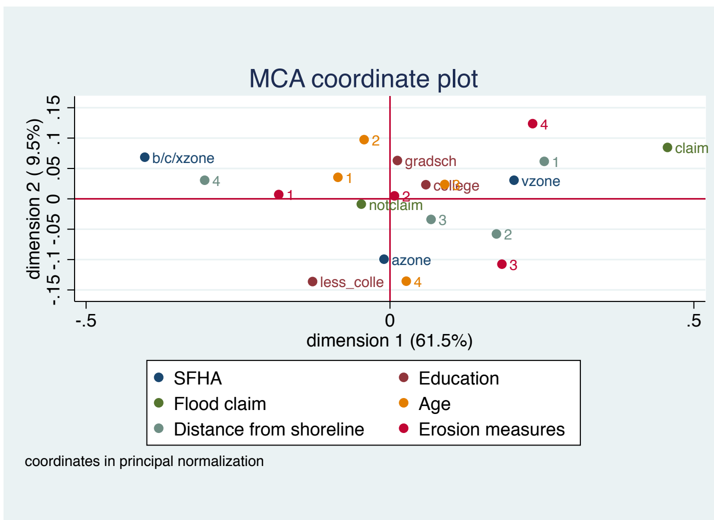

Figure 4.3: MCA analysis of risk perception

Table 4.4 presents the regression results of joint estimation of flood and erosion insurance demand for linear and exponential specifications before including risk perception. The Wald statistics of correlation between errors of two equations in both linear and exponential models are statistically significant, which denotes the dependence of flood and erosion insurance decision for this sample

disaggregated version of SFHA (vzone, azone, b/c/xzone) instead of 100-year flood zone indicator in Table 4.3. We generate variable of erosion measures based on the number of erosion measures that individual takes using the same approach.

and justify the use of bivariate normal distribution that improves the efficiency of regression (last row in Table 4.4). In addition to the significant coefficient of insurance premium with the expected negative sign (Browne and Hoyt, 2000; Kriesel and Landry 2004; Landry and Jahan-Parvar, 2011), the model selection tool of Bayesian Information Criteria shows that the exponential model performs better in fitting the data. The marginal effects of flood and erosion insurances, in the exponential specification, is -0.13 and -0.10, respectively (-0.07 and -0.02 in the linear model). Therefore, a 1% increase in insurance premium per $100 covered asset value will decrease the probability of buying flood insurance by 13% and erosion insurance by 10%. Conform with previous studies that estimate a small income effect for the insurance product (Atreya et al. 2015), we find positive income effect of 0.08 (0.04) for flood (erosion) insurance demand. As expected, mandatory flood insurance and erosion mitigating measures that are main determinants of insurance decision increase the likelihood of buying insurance by 0.29 and 0.04 for flood and erosion respectively. Consistent with the result of Botzen and van den Bergh (2012), we find no significant relationship between the elevation of property relative to floodplain and the insurance decision and find that owners of properties closer to shoreline have a higher probability of buying both flood and erosion insurance. While locating in high and moderate risk SFHA areas increase the likelihood of purchasing flood insurance, it does not have a significant impact on the erosion insurance purchasing decision in the exponential model.

Table 4.4: Multi-peril insurance demand (without joint risk perception)

	(1)	(2)	(3)	(4)
	Linear specification		Exponential specification	
Variables	Flood insurance demand	Erosion insurance demand	Flood insurance demand	Erosion insurance demand
Flood coverage premium	-0.226			
	(0.143)			
Erosion coverage premium		-0.099***		

	(1)	(2)	(3)	(4)
		(0.011)		
Log (Flood coverage premium)			-0.428***	
			(0.138)	
Log (Erosion coverage premium)				-0.388***
				(0.019)
Education (Graduate school/ College degree)	0.158	-0.017	0.167	-0.102
	(0.206)	(0.190)	(0.210)	(0.180)
Age	-0.026***	-0.008	-0.025***	-0.009
	(0.003)	(0.008)	(0.003)	(0.008)
Log (income)	0.266***	0.236***	0.245***	0.234***
	(0.049)	(0.076)	(0.054)	(0.064)
Mandatory flood insurance	0.852***		0.871***	
	(0.193)		(0.197)	
Erosion mitigating measure		0.214**		0.280***
		(0.099)		(0.100)
Distance from shoreline	-0.052***	-0.052*	-0.053***	-0.078**
	(0.013)	(0.031)	(0.015)	(0.037)
Oceanfront	0.282	0.138	0.252	0.175
	(0.174)	(0.181)	(0.168)	(0.198)
Elevation	0.001	-0.013	-0.011	-0.022
	(0.019)	(0.014)	(0.022)	(0.015)
vzone	0.772**	0.175	0.973***	0.047
	(0.312)	(0.330)	(0.276)	(0.350)
Azone	0.708***	0.430**	0.642***	0.340
	(0.165)	(0.191)	(0.180)	(0.257)
Erosion rate	0.014	-0.006	0.007	0.003
	(0.023)	(0.009)	(0.021)	(0.012)
Constant	-1.375***	-3.054**	-1.692***	-3.299***
	(0.509)	(1.462)	(0.603)	(1.252)
Rho Constant	0.155*		0.246***	
	(0.080)		(0.083)	
Observation	1207	1207	1207	1207
BIC	4757		4404	

Notes: Standard errors in parentheses are clustered at county level. All regressions include county fixed effects and an indicator for missing value of income variable. All regressions are estimated with the sampling weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Regarding the BIC analysis that favors exponential specification, we present the regression results of four bivariate regression analyses of exponential specification (Table 4.5): 1) including joint risk perception variables (column 1 and 2), incorporating MCA analysis (column 3 and 4), and 3) including relevant marginal risk perception insurance demand models (column 5 and 6).[43] As we

[43] The estimation results of linear specification are available upon request.

hypothesized, the estimated coefficient of joint risk perception parameter is significant with a positive impact (marginal impact equals 1.60 and 0.62 for flood and erosion, respectively). This suggests that higher risk perception formed by a complete set of information on correlated hazards contributes to higher demand and ultimately higher penetration rate in the insurance market.

Comparing the estimated coefficients (and the marginal effects) of flood and erosion insurance premiums in Table 4.4 and Table 4.5 (columns 3 and 4) denotes that joint risk perception increases the marginal effect of flood insurance demand (2 percentage point increase from 13% to 15%) and has no impact on erosion insurance purchasing decision. Stretching our analysis by utilizing multiple correspondence analysis provides the same result for the erosion insurance but leads to a more accurate estimation of flood insurance by capturing the negative impact of age, that were suppressed in the previous model due to multicollinearity of socio-demographic variable and risk perception parameter.

Table 4.5: Multi-peril insurance demand (with joint risk perception)

	(1)	(2)	(3)	(4)	(5)	(6)
	Joint risk perception		Joint risk perception & MCA		Marginal risk perception & MCA	
	Flood	Erosion	Flood	Erosion	Flood	Erosion
Log (Flood coverage premium)	-0.462^{***}		-0.481^{***}		-0.458^{***}	
	(0.125)		(0.135)		(0.125)	
Log (Erosion coverage premium)		-0.392^{***}		-0.391^{***}		-0.390^{***}
		(0.018)		(0.022)		(0.022)
Education (Graduate/College)	-0.121	-0.266^{*}	-0.059	-0.202^{*}	-0.001	-0.190
	(0.344)	(0.156)	(0.243)	(0.149)	(0.235)	(0.148)
Age	0.001	0.006	-0.032^{***}	-0.013	-0.031^{***}	-0.012
	(0.015)	(0.013)	(0.003)	(0.008)	(0.003)	(0.008)
Log (income)	0.245^{***}	0.237^{***}	0.266^{***}	0.241^{***}	0.279^{***}	0.237^{***}
	(0.053)	(0.066)	(0.058)	(0.066)	(0.059)	(0.065)
Mandatory flood insurance	0.857^{***}		0.876^{***}		0.863^{***}	
	(0.198)		(0.205)		(0.210)	

Erosion mitigating measure		0.184*		0.165*		0.176**
		(0.098)		(0.087)		(0.083)
Distance from shoreline	0.038	-0.028	0.038	-0.036	-0.007	-0.039
	(0.053)	(0.037)	(0.024)	(0.027)	(0.026)	(0.026)
Oceanfront	0.183	0.129	0.192	0.141	0.128	0.157
	(0.176)	(0.212)	(0.166)	(0.215)	(0.189)	(0.211)
Elevation	-0.008	-0.021	-0.011	-0.022	-0.008	-0.022
	(0.022)	(0.016)	(0.022)	(0.015)	(0.024)	(0.015)
vzone	0.551***	-0.221	0.435**	-0.233	0.900**	-0.227
	(0.163)	(0.307)	(0.261)	(0.381)	(0.450)	(0.393)
Azone	0.243*	0.108	0.319*	0.189	0.724**	0.163
	(0.128)	(0.245)	(0.168)	(0.326)	(0.349)	(0.354)
Erosion rate	0.000	-0.000	-0.005	-0.001	-0.006	-0.001
	(0.022)	(0.012)	(0.019)	(0.012)	(0.017)	(0.012)
Flood-erosion risk perception	5.401**	2.903**	6.491***	2.946**		
	(2.476)	(1.148)	(1.035)	(1.275)		
Flood risk perception					83.692***	
					(30.348)	
Erosion risk perception					-35.240**	1.502*
					(14.095)	(0.889)
Constant	4.090**	-4.628***	-2.49***	-3.573***	-11.523***	-3.723***
	(1.682)	(1.637)	(0.645)	(1.306)	(3.108)	(1.384)
Rho Constant	0.229**		0.224**		0.209**	
	(0.090)		(0.095)		(0.101)	

Notes: Notes: Standard errors in parentheses are clustered at county level. All regressions include county fixed effects and an indicator for missing value of income variable. All regressions are estimated with the sampling weights. Estimated parameters and standard errors obtained from 1000 replications using bootstrap procedure (Efron and Tibshirani, 1986). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.6 summarizes the median willingness to pay for two bundled insurance products for four specifications in Table 4.5. The choice between mean and median willingness to pay is important when mean and median of the distribution of WTP does not coincide. As Hanemann (1989) suggests in his paper, "the choice between the two, indeed, can be nontrivial" as mean is "more sensitive to skewness or kurtosis in the original data." Therefore, we present median WTP (mean WTP in Appendix C) for exponential (linear) WTP model. We investigate the welfare gain of bundled insurance product for oceanfront residents and individual who are not mandated to buy flood insurance.

Table 4.6: Welfare change analysis (median WTP)

	Median WTP (Exponential WTP function)			
	All	Oceanfront =1	Mandatory flood insurance = 0	Erosion measures= 1
Flood	1.15	3.95	0.88	1.27
Erosion	0.12	0.25	0.12	0.16
Flood (joint risk perception)	1.13	3.65	0.88	1.43
Erosion (joint risk perception)	0.12	0.25	0.12	0.16
Flood (marginal risk perception)	1.24	4.62	0.96	1.65
Erosion (marginal risk perception)	0.12	0.25	0.12	0.16

Note: all willingness to pay measures are significant at 0.01. Krinsky and Robb confidence interval is utilized for the significance test.

In the linear specifications, we find negative mean willingness to pay for erosion insurance (presented in Appendix C), while the median WTP estimated from exponential specifications sits in a reasonable range for both products. Controlling for the joint risk perception in the models, equivalent to better risk communication measures, does not increase the median willingness to pay for the whole sample. Mapping the indicator of individual's concerns about flood and erosion risk from survey to marginal flood and erosion probability function increases the WTP of oceanfront residents for the flood insurance. Coupling the information from the estimation of WTP statistics in Table 4.5 and the estimated coefficients of risk perception in Table 4.4 provides an insight on the importance of bundling and diversifying insurance products, especially, for different groups of NFIP policyholders. Proposing multi-peril insurance product reduces the uncertainty associated with correlated hazards and increases the likelihood of buying insurance products to protect against the associated welfare loss. Most importantly, while owners of oceanfront properties are willing to pay a higher premium for the bundled products, property owners who are not mandated to buy flood insurance are eager to contribute to forming an erosion insurance market coupled with NFIP.

Moreover, property owners who have engaged in some erosion mitigation measures are willing to pay a higher amount for erosion insurance. We conclude larger and statistically different willingness to pay for residents of oceanfront properties, as well as slight differences between those who are not required to buy insurance and the whole sample.

4.7 Discussion

The multi-peril coastal hazard insurance is a useful mitigation measure to address the erosion hazard in coastal areas. This insurance product that has been used widely to protect agricultural products against natural hazards (e.g. Multi-peril crop insurance) is introduced as an important risk transfer mechanism that addresses underlying reasons of insurance demand and supply markets inefficiencies and offers solutions to disputes between insurers and insureds in splitting the total damages between different sources of damage.

In this study, we estimate the economic value of a flood and erosion bundled insurance product to reduce the risk of multi-peril natural hazards for the property owners. Bundling insurance products increases insurance market penetration and leads to welfare increase if the flood and erosion insurances are sold together for erosion-prone areas such as coastal area (i.e. pure bundling). As the empirical evidence illustrates two bundled insurance products are complements with positively correlated reservation values. Residents of coastal areas have positive willingness to pay for both flood and erosion insurance products and the bundled products add value to each other which allows for price of the bundled product to be higher than the sum of the price of the components.

Focusing on erosion hazard in the coastal areas is especially relevant, as it can undermine waterfront houses, businesses, and public facilities over time. Currently, there are many shortcomings in addressing and incorporating erosion risk into insurance markets and there is no evidence of the existence of a private insurance market that provides indemnification against erosion risk. Evaluation of erosion hazards illustrates that risk of erosion and flooding are comparable and erosion may be responsible for the destruction of one out of four houses within 500 feet of U.S. shoreline in a 60-year time horizon (H.J Heinz 2000). NFIP as it stands today does not map erosion hazard areas, and the insurance premiums of homeowners in erosion-prone areas do not differ from other NFIP policyholders. Regarding the lack of private insurance markets for erosion hazard and high erosion risk in coastal areas, we show that residents of coastal regions demand multi-peril coastal hazard insurance and they would be willing to pay for the addition of erosion insurance to NFIP. This result can inform policy makers that bundled insurance product can be offered to population of interest in coastal areas after addressing shortcomings of NFIP in including the erosion risk.

Our investigation illustrates that homeowners whose properties are located in Special Flood Hazard Area, those who have filed insurance claims, as well as those who live in communities with local erosion mitigation measures have higher joint flood-erosion risk perception, and their higher risk perception can lead to larger probability of buying bundled insurance products. A reason behind low penetration rate of insurance product is that individual decision makers' risk perception is lower that the threshold level of concern (Kunreuther and Pauly 2004). Bundling insurance products and informing individual of the joint risk of two natural hazard serves to improve market penetration rate and helps individuals to pass the intuitive thinking stage and engage in deliberative thinking that deals with the unfamiliar risk (Kunreuther 2017). Regarding individuals' tendency to view insurance as an investment rather than protective measure (Kunreuther 2017), another upside of multi-peril insurance is to improve the NFIP enforcement in hazard-prone areas by reducing the number of lapsed policies as individuals are more likely to file an insurance claim when more than one peril is included in the insurance. When multiple hazards exist, and insureds are willing to pay higher premium to protect themselves against multiple hazards risk, multi-peril insurance is a mechanism to obtain the principle of risk-rated premium.

CHAPTER 5

CONCLUSION

In this dissertation research, we look at different angles of impacts of environmental amenities and disamenities on individual well-being. We indicate how the welfare gain/losses as result of a change in the quality/quantity of environmental amenities can alter individuals decision making; from moving to a location with more abundance of environmental amenities to purchasing a multi-hazard insurance that protects against the correlated hazards risk.

In the second chapter of this dissertation, we explore the method of SWB to illustrate how individuals place value on environmental characteristics of a location and adapt their location decision leading to a further uneven distribution of urban disamenities across space. We match individual-level survey data from the Behavioral Risk Factor Surveillance System (BRFSS) that includes a life-satisfaction question, to county-level local amenities between 2005 and 2010. Consistent and comparable with the interurban hedonic spatial models (Rosen 1979 and Roback 1982, 1988) that generate objective measures of quality of life based on wage and housing price differentials, we investigate the spatial variation of subjective well-being across the United States and focus on both compensating factors (individual and relative income and housing value) and local, environmental and climate amenities. Our results conform with national and international studies of analyzing the "geography of happiness" and find that the self-reported SWB varies widely across space. We then show that local amenities, specifically environmental amenities, do explain a sizable fraction of the variation in SWB both across and within U.S. counties and compare the relative importance of amenity types in explaining regional differences in SWB. We show that for multiple amenities their estimated total and partial effects (conditional on individual income, housing values, and county median income) on life satisfaction are similar and different from zero, reinforcing the intuition that labor and housing markets are not fully capitalizing their impacts on life satisfaction.

In the third chapter, we match forty-two billion-dollar disasters with individual survey data from the Behavioral Risk Factor Surveillance System between 2005 and 2010 to estimate the effect of extreme weather events on the subjective well-being of U.S. residents. Compared to post-disaster damage estimates and to traditional methods that measure impacts of disasters on individual welfare (e.g. revealed preference methods), the SWB approach directly focuses on the less tangible negative consequences of weather and climate events, making it a potentially useful additional tool for policymakers to assist communities in assessing their vulnerabilities to the impacts of climate in the areas of human health and planning strategies for adapting to the changing climate. Our results indicate that natural disasters have a negative and robust impact on subjective well-being in the affected communities, and that this impact decays after 6 to 8 months after the event. Severe storms are the main culprit in the reduction of individual life satisfaction in our sample. We then investigate the attenuating impact of health care access, natural-peril insurance, and governmental assistance programs and find a partial compensating role for both private and public protective measures.

In the fourth chapter of this dissertation, we take a step further in quantifying the impact of natural disasters at the micro level; we combine revealed and stated preference data on different hazard insurance products to estimate welfare effects of bundled insurance product for a sample of residents of the southeast US coast. The issue of allocating damages between multiple correlated natural hazards, extended litigation of insurance claims after such incidences, and two very important goals of reaching a risk-rated market premium and minimizing NFIP staggering debt, make the proposal of broadening NFIP to allow policyholders to purchase optional erosion coverage very important. Our results obtained from a bivariate regression analysis, indicate that households who live in the coastal zone place a higher value on the multi-peril hazard insurance. While individual use the insurance premium as a risk signaling mechanism, their information of likelihood of natural hazard is limited. We empirically estimate the risk perception of a decision maker, as an alternative to objective risk estimates, based on individual characteristics. We then test the effect of risk perception (subjective risk assessment) on individuals' decision to purchase multi-peril hazard insurance and conclude that higher risk perception leads to higher probability of purchasing multi-peril insurance, specially for oceanfront residents.

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APPENDICES

A. Multi-level regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	Env. & climate amenities	All amenities	All amenities	Env. & climate amenities	All amenities	All amenities
VARIABLES	Without compensating factors	Without compensating factors	With compensating factors	Without compensating factors	Without compensating factors	With compensating factors
Education	-0.0393***	-0.0410***	-0.0348***	-0.0391***	-0.0410***	-0.0346***
	(0.0015)	(0.0018)	(0.0022)	(0.0015)	(0.0018)	(0.0022)
Education^2	0.0019***	0.0020***	0.0013***	0.0019***	0.0020***	0.0013***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Marital status (ref: Never married)						
Married	0.2298***	0.2327***	0.1716***	0.2297***	0.2325***	0.1716***
	(0.0015)	(0.0017)	(0.0020)	(0.0015)	(0.0017)	(0.0020)
Divorced	0.0010	0.0036*	0.0030	0.0009	0.0035*	0.0030
	(0.0018)	(0.0021)	(0.0023)	(0.0018)	(0.0021)	(0.0023)
Widowed	0.0579***	0.0596***	0.0503***	0.0578***	0.0595***	0.0502***
	(0.0020)	(0.0023)	(0.0026)	(0.0020)	(0.0023)	(0.0026)
Separated	-0.0728***	-0.0658***	-0.0621***	-0.0729***	-0.0660***	-0.0622***
	(0.0032)	(0.0038)	(0.0042)	(0.0032)	(0.0038)	(0.0042)
Cohabit	0.0929***	0.0951***	0.0685***	0.0932***	0.0954***	0.0686***
	(0.0031)	(0.0035)	(0.0040)	(0.0031)	(0.0035)	(0.0040)
Race (ref: White)						
Black / African American	0.0394***	0.0380***	0.0598***	0.0362***	0.0363***	0.0584***
	(0.0017)	(0.0020)	(0.0022)	(0.0017)	(0.0020)	(0.0022)
Asian	-0.0400***	-0.0416***	-0.0317***	-0.0397***	-0.0414***	-0.0318***
	(0.0039)	(0.0042)	(0.0049)	(0.0039)	(0.0042)	(0.0049)
Native Hawaii/ Pacific Islander	0.0201*	0.0263**	0.0439***	0.0206**	0.0266**	0.0440***
	(0.0104)	(0.0114)	(0.0136)	(0.0104)	(0.0114)	(0.0136)
American Indian /Native Alaskan	0.0143***	0.0072	0.0297***	0.0147***	0.0075	0.0303***
	(0.0038)	(0.0046)	(0.0052)	(0.0038)	(0.0046)	(0.0052)
Other	-0.0008	0.0023	0.0232***	-0.0007	0.0020	0.0233***
	(0.0022)	(0.0025)	(0.0030)	(0.0022)	(0.0025)	(0.0030)
Age (ref: 18-24)						
25 to 34	-0.0743***	-0.0748***	-0.0613***	-0.0745***	-0.0749***	-0.0615***
	(0.0029)	(0.0033)	(0.0039)	(0.0029)	(0.0033)	(0.0039)
35 to 44	-0.0824***	-0.0815***	-0.0859***	-0.0824***	-0.0815***	-0.0861***
	(0.0028)	(0.0033)	(0.0039)	(0.0028)	(0.0033)	(0.0039)
45 to 54	-0.0693***	-0.0695***	-0.0789***	-0.0693***	-0.0695***	-0.0790***

	(0.0028)	(0.0033)	(0.0039)	(0.0028)	(0.0033)	(0.0039)
55 to 64	0.0004	-0.0023	-0.0066*	0.0004	-0.0023	-0.0068*
	(0.0029)	(0.0033)	(0.0039)	(0.0029)	(0.0033)	(0.0039)
65 or older	0.0636***	0.0639***	0.0823***	0.0637***	0.0640***	0.0823***
	(0.0030)	(0.0035)	(0.0042)	(0.0030)	(0.0035)	(0.0042)
Employment status (Ref: Employed)						
Self-employed	0.0026	0.0020	0.0093***	0.0026	0.0019	0.0092***
	(0.0016)	(0.0019)	(0.0021)	(0.0016)	(0.0019)	(0.0021)
Unemployed- > 1 year	-0.2551***	-0.2586***	-0.1946***	-0.2550***	-0.2586***	-0.1947***
	(0.0030)	(0.0035)	(0.0040)	(0.0030)	(0.0035)	(0.0040)
Unemployed- < 1 year	-0.2202***	-0.2239***	-0.1773***	-0.2201***	-0.2239***	-0.1773***
	(0.0028)	(0.0032)	(0.0036)	(0.0028)	(0.0032)	(0.0036)
Homemaker	0.0196***	0.0197***	0.0386***	0.0195***	0.0197***	0.0386***
	(0.0018)	(0.0020)	(0.0024)	(0.0018)	(0.0020)	(0.0024)
Student	-0.0023	-0.0005	0.0202***	-0.0022	-0.0005	0.0203***
	(0.0035)	(0.0041)	(0.0048)	(0.0035)	(0.0041)	(0.0048)
Retired	0.0328***	0.0337***	0.0630***	0.0327***	0.0335***	0.0628***
	(0.0015)	(0.0017)	(0.0020)	(0.0015)	(0.0017)	(0.0020)
Unable to work	-0.2050***	-0.2118***	-0.1505***	-0.2055***	-0.2119***	-0.1506***
	(0.0021)	(0.0025)	(0.0029)	(0.0021)	(0.0025)	(0.0029)
General Health (ref: Poor)						
Fair	0.2094***	0.2157***	0.2164***	0.2098***	0.2161***	0.2167***
	(0.0022)	(0.0027)	(0.0031)	(0.0022)	(0.0027)	(0.0031)
Good	0.3597***	0.3681***	0.3550***	0.3602***	0.3685***	0.3554***
	(0.0021)	(0.0026)	(0.0030)	(0.0021)	(0.0026)	(0.0030)
Very good	0.5388***	0.5488***	0.5239***	0.5395***	0.5492***	0.5243***
	(0.0022)	(0.0026)	(0.0030)	(0.0022)	(0.0026)	(0.0030)
Excellent	0.6836***	0.6949***	0.6622***	0.6843***	0.6954***	0.6625***
	(0.0023)	(0.0027)	(0.0032)	(0.0023)	(0.0027)	(0.0032)
Sex (ref: Female)						
Male	-0.0149***	-0.0162***	-0.0253***	-0.0148***	-0.0161***	-0.0252***
	(0.0009)	(0.0011)	(0.0012)	(0.0009)	(0.0011)	(0.0012)
Income (Ref: less than $10K)						
$10K-$15K			0.0245***			0.0244***
			(0.0036)			(0.0036)
$15K-$20K			0.0557***			0.0555***
			(0.0034)			(0.0034)
$20K-$25K			0.0689***			0.0687***
			(0.0034)			(0.0034)
$25K-$35K			0.0931***			0.0930***
			(0.0033)			(0.0033)
$35K-$50K			0.1338***			0.1336***
			(0.0033)			(0.0033)
$50K-$75K			0.1851***			0.1849***
			(0.0034)			(0.0034)
More than $75K			0.2685***			0.2682***
			(0.0034)			(0.0034)

Mean Min. Jan Temp.	0.0008***	0.0007***	0.0007***	-0.0004***	-0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Mean Max. Jul Temp.	-0.0047**	-0.0068***	-0.0094***	0.0008	0.0005	-0.0034
	(0.0019)	(0.0026)	(0.0031)	(0.0019)	(0.0026)	(0.0031)
Mean Max. Jul Temp.^2	0.0000***	0.0000***	0.0001***	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Precipitation	0.0003***	0.0002***	0.0003***	-0.0001	-0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Federal recreation land	0.0001	0.0000	0.0003***	0.0001	0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Coastal	-0.0093***	-0.0092***	-0.0052*	-0.0006	-0.0010	-0.0014
	(0.0022)	(0.0025)	(0.0027)	(0.0023)	(0.0024)	(0.0027)
Mean elevation	-0.0000	-0.0000**	-0.0000	-0.0000	-0.0000***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sunshine	0.0009***	0.0009***	0.0008***	0.0010**	0.0009**	0.0007
	(0.0001)	(0.0001)	(0.0002)	(0.0005)	(0.0004)	(0.0004)
Unhealthy day		-0.0002***	-0.0002***		-0.0001	-0.0001*
		(0.0000)	(0.0001)		(0.0000)	(0.0000)
Mean travel time to work		0.0002	0.0004		-0.0000	-0.0002
		(0.0002)	(0.0003)		(0.0002)	(0.0003)
Unemployment rate		-0.0007	-0.0007		-0.0004	-0.0001
		(0.0004)	(0.0005)		(0.0004)	(0.0005)
Population density		-0.0001***	-0.0001**		-0.0001***	-0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Urban area (%)		-0.0003***	-0.0004***		-0.0004***	-0.0005***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Metropolitan area		-0.0189***	-0.0283***		-0.0164***	-0.0282***
		(0.0052)	(0.0057)		(0.0045)	(0.0053)
Micropolitan area		-0.0109**	-0.0165***		-0.0084*	-0.0155***
		(0.0053)	(0.0059)		(0.0047)	(0.0054)
Pupil-teacher ratio		-0.0011***	-0.0006		0.0015**	0.0014*
		(0.0004)	(0.0005)		(0.0007)	(0.0008)
Constant	3.1141***	3.2354***	3.3136***	2.9268***	2.9307***	3.0761***
	(0.0779)	(0.1081)	(0.1285)	(0.0814)	(0.1106)	(0.1312)
Observations	1,811,463	1,328,031	1013458	1,811,463	1,328,031	1,013,458
BIC	2285650	2285650	1732857	3116854	2285375	1732698

B. Billion-dollar weather and climate disasters in the U.S. from 2004 to 2010

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

19	June 2008	Midwest/Mid Atlantic Severe Weather	IA, IL, IN, KS, NE, MI, MN, MO, OK, WI, MD, VA, and WV	1,009	$1.6	18
20	May 2008	Midwest Tornadoes Severe Weather	IA, IL, IN, KS, NE, MI, MN, MO, OK, WI, MD, VA, and WV	602	$3.3	13
21	April 2008	Southern Severe Weather	AR, OK, and TX	299	$1.1	2
22	March 2008	Southeast Tornadoes	GA and SC	142	$1.2	5
23	February 2008	Southeast Tornadoes and Severe Weather	AL, AR, IN, KY, MS, OH, TN, and TX	491	$1.3	57
24	Summer-Fall 2007	Western/Eastern Drought/Heatwave	ND, SD, NE, KS, OK, TX, MN, WI, IA, MO, AR, LA, MS, AL, GA, NC, SC, FL, TN, VA, WV, KY, IN, IL, OH, MI, PA, NY	1,176	$4.0	15
25	Summer 2007	Western Wildfires	AK, AZ, CA, ID, UT, MT, NV, OR, and WA	142	$3.1	12
26	April 2007	East/South Severe Weather and Flooding	CT, DE, GA, LA, ME, MD, MA, MS, NH, NJ, NY, NC, PA, RI, SC, TX, VT, and VA	701	$2.9	9
27	April 2007	Spring Freeze	AL, AR, GA, IL, IN, IA, KS, KY, MS, MO, NE, NC, OH, OK, SC, TN, VA, and WV	1,049	$2.3	0
28	January 2007	California Freeze	CA	50	$1.6	1
29	2006	Numerous Wildfires	AK, AZ, CA, CO, FL, ID, MT, NM, NV, OK, OR, TX, WA, and WY	319	$1.8	28
30	Spring-Summer 2006	Midwest/Plains/Southeast Drought	ND, SD, NE, KS, OK, TX, MN, IA, MO, AR, LA, MS, AL, GA, FL, MT, WY, CO, and NM	839	$7.1	0
31	June 2006	Northeast Flooding	NY, PA, DE, MD, NJ, and VA	168	$1.8	20
32	April 2006	Midwest and Midwest/Southeast	OK, KS, MO, NE, KY, OH, TN, IN,	1,330	$4.7	27

		Tornadoes	MS, GA, AL, AR, KY, TX, IA, IL, and WI			
33	March 2006	Severe Storms and Tornadoes	AL, AR, KY, MS, TN, TX, IN, KS, MO, and OK.	755	$1.5	10
34	September 2005	Hurricane Rita	FL, AL, MS, LA, AR, and TX	671	$22.6	119
35	Spring-Summer 2005	Midwest drought	AR, IL, IN, MO, OH, and WI	269	$1.8	0
36	August 2005	Hurricane Katrina	AL, MS, FL, TN, KY, IN, OH, and GA	516	$152.5	1,833
37	July 2005	Hurricane Dennis	FL, AL GA, MS, and TN.	344	$3.1	15
38	September 2004	Hurricane Jeanne	GA, SC, NC, VA, MD, DE, NJ, PA, and NY	509	$9.5	28
39	September 2004	Hurricane Ivan	GA, MS, LA, SC, NC, VA, WV, MD, TN, KY, OH, DE, NJ, PA, and NY	780	$25.8	57
40	September 2004	Hurricane Frances	GA, SC, NC, and NY	321	$12.3	48
41	August 2004	Hurricane Charley	FL SC and NC.	147	$20.8	35
42	May 2004	Severe Storms, Hail, Tornadoes	ND, SD, NE, KS, MO, IA, MN, WI, IL, IN, MI, OH, Ok, TX, AR, LA, MS, AL, TN, KY, VA, NC, SC, GA, FL, ME, VT, NH, MA, NY, RI, CT, NJ, DE, MD, WV, PA, NY	2,223	$1.2	4

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

C. Welfare change analysis (mean WTP)

	Mean WTP (Linear WTP function)			
	All	Oceanfront =1	Mandatory flood insurance =0	Erosion measures= 1
Flood	2.11**	4.51**	1.64**	2.09**
Erosion	-3.03	-0.38	-3.04	-2.19
Flood (joint risk perception)	2.04***	4.24***	1.62***	2.26***
Erosion (joint risk perception)	-3.02	-0.39	-3.04	-2.15
Flood (marginal risk perception)	2.09***	4.34***	1.67***	2.38***
Erosion (marginal risk perception)	-2.99	-0.39	-3.01	-2.13

Notes: Krinsky and Robb confidence interval is utilized for the significance test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.