The Effects of Adaptation Measures on Hurricane Induced Property Losses

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Abstract

Escalating costs of hurricane disasters in recent decades heighten public and private concern. Federal government spends millions of dollars annually in the form of hazard mitigation and public assistance grants to help impacted communities recover. Without empirical evidence, we can say little about how effective these programs are in terms of promoting local resilience. In the paper, we investigate the roles of adaptation and mitigation in reducing economic impacts of hurricanes in terms of property loss. We conduct an empirical study of property damage in 864 counties along the Atlantic basin during 1989-2009. Controlling for important drivers of property losses given by hazard incidents, economic and population growth as well as socio-economic vulnerability, we contribute to the existing literature by explicitly accounting for a wide range of public and local adaptation measures. Our results suggest that physical and socio-economic vulnerability are primary factors explaining high damages from hurricanes. We find clear evidence of the importance of regulatory-based loss mitigation strategies as exhibited by improved building codes and effectiveness of enforcement. Results suggest that *where to build* (zoning, land-use planning, etc.) is a significant policy complimented by *how to build* (building codes, retrofitting, etc.). Major structural and infrastructural projects were found to exacerbate property losses suggesting evidence of moral hazard, induced development or protective capacity limits of structural measures. Overall, the most efficient disaster loss mitigation strategy entails coordinated actions of federal and local government coupled with private self-insurance initiatives and is highly skewed towards non-structural projects.

Keywords: natural disasters, hurricanes, property losses, damages, types of adaptation measures, FEMA, public assistance and hazard mitigation grants

I. Introduction

Hurricanes represent one of the costliest natural catastrophes in the United States. At the beginning of the 20th century, decadal total number of hurricane fatalities was 8,734 with the corresponding damage cost of $1.45 billion (in year 2000 dollars) (Sheets and Williams, 2001). The last decade figures show that deaths have decreased by a factor of 35 whereas costs have risen by a factor of 39 (Figures 1 and 2). Over time, hurricane fatalities have become less of a concern, partially attributed to improved warning and weather forecasting systems in coastal counties (Sadowski and Sutter, 2005). This declining trend in loss of human life, however, has not been accompanied by a decrease in property damage. Increased intensity and frequency of Atlantic basin hurricanes is considered to be partially responsible for direct as well as indirect economic losses. Much property loss has also been inflicted because of increased population, rising standards of living and the consequent accumulation of wealth in these coastal areas (Pielke, et al., 2008).

If recent socio-economic developments persist (rising coastal population and increase in wealth level) coupled with geophysical trends of hurricane intensities, damage figures will likely grow astronomically. Pielke et al. (2008) find that the normalized damages of hurricanes provides an important "*warning*" message for policy makers: *"Potential damage from storms is growing at a rate that may place severe burdens on society. Avoiding huge losses will require either a change in the rate of population growth in coastal areas, major improvements in construction standards, or other mitigation actions. Unless such action is taken to address the growing concentration of people and properties in coastal areas where hurricanes strike, damage will increase, and by a great deal, as more and wealthier people increasingly inhibit these coastal locations".*

An obvious agenda for researchers and policy makers involves decisions on loss mitigation strategies and plans to lessen these economic impacts. The domain of potential public and private coping and adaptation options is large. It goes beyond measures designed to mandate and enforce stringent regulatory policies such as building codes, hazard planning, land zoning and development regulation. Often, these measures are immensely costly and involve providing public protection via implementing and investing in major retrofitting and/or structural projects such as dams, levees, acquisition of private property, etc. In addition to these proactive measures, devastating natural disasters elicit post-disaster recovery and assistance programs primarily aimed to provide immediate relief to impacted communities.

Federal government spends millions of dollars annually to help communities recover from severe disasters. Since 1989 Federal Emergency Management Agency (FEMA) has spent more than 13 billion dollars to help communities implement long term hazard mitigation projects. Approximately 76% of total mitigation grant funding have been allocated for hurricane, storm and flood related disasters. Even more was spent for public assistance projects. Around 45 billion dollars (in 2005$) was given to impacted communities, since 1999, in the form of immediate assistance to help with disaster recovery.[1] Approximately eighty percent of these funds were given in response to hurricane, flood or severe storm related events (Figures 3 and 4).

[1] The figures are based on Hazard Mitigation Grant Program (HMGP) and Public Assistance grants programs initiated under Robert T. Stafford Disaster Relief and Emergency assistance Act, which was passed in 1988.

Furthermore, these figures are higher when accounting for non-disaster governmental transfers, which are likely to increase substantially after major disasters (Deryugina, 2011).[2] These numbers are striking and certainly raise public concern especially as the frequency and severity of hurricanes are projected to increase in the future.

Without empirical evidence, we can say little about how effective these hazard mitigation and assistance programs are in terms of promoting local resilience. It seems perfectly reasonable to assume that protective/adaptive measures should mitigate losses; however, the impact of different measures on reducing losses is unclear. For instance, an adverse impact of structural projects (dams, levees, etc.) could occur for several reasons. First, if the severity of hazards exceeds designed capacity of these protective structures, their failure could lead to an even greater catastrophic outcome (Mileti, 1999). Second, the effectiveness of some protective measures are not immediately obvious. Often, they are not directly realized due to the behavioral interactions of involved parties (private and public sector). Providing protective public infrastructure is argued to encourage private development resulting in more wealth exposure to risk which subsequently translates into higher damages in risk prone areas (Kousky et al, 2006; Kousky and Olmstead, 2010). Perverse incentives resulting from government protection on private behavior is also suggested through experience with some government relief programs. The expectation of post disaster recovery/relief assistance is argued to create the belief that financial assistance will be supplied if the disaster re-occurs. Heuristic attitude of individuals to risk and limited financial liability for disaster loss result in under-investment in private protective measures (Kunreuther, 2001, Lewis and Nickerson, 1989).

The majority of previous studies of hurricane damages account for only physical and economic exposure. Consequently the results of these studies are based either on a strong assumption of no adaptation (Nordhaus, 2010) or, in some cases, adaptation is inferred from a time trend or a physical event (Sadowski and Sutter, 2005, 2008). Moreover, these past studies overlook many other factors that potentially contribute to the transformation of natural hazards to natural disasters or conversely, loss mitigation. While other scholars have developed theoretical frameworks in which they delineate different types of adaptation measures and their implications in terms of mitigating losses (self-insurance, self-protection or market insurance, risk-reducing, risky, etc.), they all acknowledge the limitations of theoretical assumptions and unequivocally call for empirical examination of the protectiveness of these measures. (Ehrlich and Becker, 1972; Lewis and Nickerson, 1989; Shogren and Crocker, 1991; Quiggin, 1992).

To address these limitations and to address the existing knowledge gap between theory and empirics, this paper investigates the impact of various protective/defensive and adaptive/coping measures on hurricane-induced property losses within U.S. counties by providing answers to the following questions:

1. What types of policies are most effective to mitigate property loss from hurricanes?
2. Do certain measures (particularly structural projects) exacerbate losses?
3. Does public provision of protection create perverse incentives for private adaptation and lead to moral or charity hazard?

We conduct an empirical study of historical property damages of 864 counties along the Atlantic coast. All have experienced property loss at least once during the 1989-2009 time period. To

[2] Deryugina (2011) suggests $654 additional non-disaster transfer of per capita in hurricane impacted counties.

measure the effectiveness of various adaptation measures implemented by federal and local governments, we control for counties' (1) geophysical exposure to hurricanes and physical vulnerability, (2) economic and demographic exposure and (3) socio-economic and infrastructure vulnerability. We adopt the definitions of adaptation measures of Fisher-Vanden et al. (2011). These types of adaptation measures encompass a series of non-structural (hazard identification, public awareness, warning systems, etc.) and structural projects (retrofitting, elevation, relocation, acquisition, dams, levees, infrastructure rehabilitation, etc.) funded through the FEMA Public Assistance and Hazard Mitigation grant programs.

Our results suggest that economic exposure and socio-economic vulnerability are primary drivers for property losses. We estimate an income elasticity of damage 8%. Nonetheless, we find that as incomes rise counties experience less property loss, suggesting increased demand for precautionary measures in wealthier communities. We also find higher unemployment rates and per capita vulnerable infrastructure exacerbate damages. Similar to past studies, results indicate strong evidence that counties with prior hurricanes suffer less property loss. Interestingly, counties where other types of disasters were declared one year before a current hurricane incident, incur on average $1.7 million less property loss from hurricanes in the following year. This finding is suggestive of the importance of timely public response measures in the form of after-shock relief and assistance activities. Additionally, we find that counties where building codes are effectively enforced experience on average $2.02 million less property loss. Results also indicate that projects funded through FEMA to improve and implement hazard planning, awareness studies and warning systems are the most effective loss mitigation activities. These findings essentially imply that information through awareness studies and warning systems are communicated effectively and likely encourage private (individual) level adaptive behavior. Restricting development, retrofitting and acquisition of private property as well as post-disaster debris clean up and assistance program provided by FEMA also exhibit significant loss-reducing effects. Investments in major structural and infrastructural projects, however, are found to exacerbate losses. This result could be evidence of moral hazard, capacity constraints of these structural projects (dams, levees, etc.) or could simply capture increased exposure to hazard risk given investment in improved infrastructure and structural projects. Overall, our results suggest that the most efficient disaster loss mitigation strategies are highly skewed towards non-structural projects.

Our work contributes to the growing literature on climate change adaptation, climate induced natural disaster and vulnerability studies in several ways. The vast majority of past studies have focused on understanding vulnerability caused by natural disasters on a global scale. Commonly, these studies account for income, population, types of hazard as well as some proxy for institutional quality (Kahn, 2005; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2008; Ward and Shively, 2011; Silbert and Useche, 2011; Schumacher and Strobl, 2011). These cross-country studies allow for a comparison of countries of various wealth and scale as well as impacts of different types of hazard and institutions. However, they are limited in that do not permit for adaptive/coping mechanism to be modeled explicitly on a grand scale. This is due to the localized nature of these measures (Horwich, 2000). Moreover, the primary argument of cross country analysis of disasters stems from the premise that poor (developing) countries are more vulnerable to natural disasters. While, this argument may be true, it does not necessarily lessen the significance of hazard severity on developed (wealthy) nations. It is indisputable that richer economies have more resources to cope and insure against natural hazards. Being rich, however, also implies more wealth at stake which potentially translates into astronomically high damage figures if the disaster is devastating. As some recent research has shown, under certain conditions, in spite of continuously improving protection, disaster losses could grow faster than wealth (Hallegatte, 2011). Studying the US coastal economy provides an opportunity to identify factors that contribute to as well as mitigate damages induced by natural hazards. Given the increased vulnerability of developing countries to extreme natural events and the lack of adaptive capacity in these countries, we expect the findings of interconnection of highly complex natural and social system in the United States would help policy makers address this issue in the context of developing nations. This information could strategically direct hazard mitigation and coping funding in the future.

While several papers have investigated disaster vulnerability within a country context and developed indirect/alternative measures of loss mitigation, to our knowledge, no study has explicitly addressed the effectiveness of private and public adaptation measures, particularly local measures. For instance, using decadal dummies Sadowski and Sutter (2005) infer historical adaptive trends and explain increased wealth exposure to be a consequence of reduced lethality of hurricanes or so-called "safe hurricanes". In another study (2008), authors propose a hypothesis that, under the assumption that mitigation measures are commonly reviewed after a disaster occurs, counties with prior land-falling hurricanes should experience fewer damages. They find some evidence that damages are reduced in counties with prior land-falling hurricanes. Nevertheless, the results were found to be insignificant for major hurricanes. This was partially justified because of the *"pressure to rebuild quickly*" which might potentially disable communities from considering mitigation efforts. Few papers have addressed the aspect of adaptation in lessening economic damages from flood or other weather related disasters, emphasizing instead on the importance of state involvement in terms of enforcing laws and regulation, building codes and structural measures (Burby, 2005; Brody et al., 2007). Our research is in line of these papers and compliments their findings by addressing a problem in a more cohesive framework by explicitly modeling the full spectrum of hurricane damage determinants. Furthermore, no paper has studied features of hazard mitigation and public assistance programs funded through FEMA. The wide range of data allows us to consider both horizontal (type I, type II, type III) as well as vertical (local, state, federal, private) dimensions of adaptation policies and compare alternative loss mitigation options. We believe, that the model generates important results in understanding the implications and effectiveness of different loss mitigation and hazard coping policies. It significantly contributes to enhancing research-based and better informed public policy decisions regarding hazard prevention/adaptation investment and enforcement regulations.

The rest of the paper is organized as follows. In section II we discuss determinants of hurricane damages; Section III provides a conceptual framework and proposed hypothesis. Section IV provides detailed description of the data used for analysis and empirical estimation strategy; Section V present results discussion and last, Section VI concludes.

II. Determinants of Hurricane Damages

Hurricanes are defined as one of the most severe forms of tropical cyclones. A storm with wind speeds of 38 mph (33kt) or less is called a tropical depression; a storm with wind speeds of 39-73 mph (34-63 kt) is called a tropical storm, whereas a storm with wind speed exceeding 74 mph (64kt) is categorized as a hurricane. The intensity of hurricane strength is measured on the Sarrif-Simpson Hurricane scale which consists of five categories. A lower number represents the weakest hurricanes in terms of wind speeds (74-95 mph or 64-82 kt), whereas the highest category is the strongest with wind speeds exceeding 155 mph (greater than 135 kt). Categorization of hurricanes in terms of wind strength does not have a one to one correspondence with the amount of damage a storm inflicts. Sometimes, lower scale hurricanes may cause more damage based on where and when they occur and the level of hazard they bring. Major hazards associated with tropical cyclones are storm surges, high winds, heavy rains/flooding and sometimes tornadoes (NOAA, 1999). Storm surge is a large dome of water that is 50 to 100 miles wide and more than 15 feet deep at its peak. It usually affects the coastline and thus represents a major threat in terms of property and human loss. Hurricane winds damage buildings and other structures, the resulting debris posing a threat to human life. Lastly, hurricanes are often accompanied by at least 6 to 12 inches of rain which results in flooding and further loss of property and human life. Occasionally, hurricanes spawn tornadoes which often develop on the fringes of the storm.

Hurricanes and earthquakes are considered two of the major causes of property damage and loss of human life. It terms of damage, hurricanes are the costliest natural catastrophes in the United States (Anthes, 1982). Many researchers believe that there has been a significant change in hurricane frequency and intensity due to climate change. Although, we find mixed results on a global scale, many scholars agree on the shift of hurricane intensities as it relates to climate in the North Atlantic basin. For example, Emanual (1987) estimates that doubling the CO_2 content in the atmosphere could increase hurricane destructiveness potential, as measured by its intensity and frequency, by 40-50%. Webster et al. (2005) detect no global trend in the storm number and intensity as it relates to increased Sea Surface Temperature (SST); however, they suggest that the North Atlantic region warns of significant increase in the number of hurricanes starting in 1995. Nordhaus (2010) also hypothesizes that the sea-surface temperature increases upper limit of cyclone wind speed and that an equilibrium doubling of CO_2-equivalent atmospheric concentrations increases hurricane damages by 0.06 percent of GDP. Moreover, the distribution of extremely costly storms is projected to increase sharply in the future as a result of global warming. The damages at the 99th percentile of years are estimated to be 0.7 percent of GDP without warming as compared to 1.4 percent of GDP with global warming.[3] Reproducing synthetic hurricane tracks, Hallegatte (2007) also finds that the annual probability of land-falling hurricanes, especially those of the strongest categories, is increasing resulting in an increase in economic losses.

Defining economic damage as a function of sustained wind speed has resulted in a crude approximation of hurricane-induced economic losses and provides only partial answer why damages have escalated in recent decades. Emanual (2005) suggests the actual monetary loss due to wind storms to rise by the power of cube of the maximum wind speed. Although not a perfect measure of the threat of economic loss, he argues that this measure is a better approximation of

[3] Nordhaus, 2011 defines the damages for the 99th percentile of years as the value of damages that exceeds 99 percent of years

loss than the simple measures of storm frequency or intensity. On the other hand, Nordhaus (2010), based on the simple regression between normalized damages (normalized by GDP) and maximum wind speed, estimates the regression coefficient for the maximum wind speed to be approximately eight. As such, he denotes this relationship as the "*eights-power law of damages*" and argues that highly non-linear relationship between physical damages and wind and water stress is a primary reason for the super-high elasticity of wind damages. Strobl (2008), employing the normalized damages of hurricanes developed by Pielke et al. (2008), shows that the selection of power is sensitive to the choice of normalized damages. His findings confirm Emanuel's power of the wind dissipation index of cube.

A key assumption made in the estimation of wind speed power as it relates to damages is the assumption of no adaptation and other constituents of disaster risk, relaxation of which could significantly alter the results. Hurricane wind speed and frequencies comprise the most significant measurements but they represent only two reasons why damages vary across time and space. This highly complex natural system is a combination of size, intensity, speed and direction, which interacts with the socio-economic system non-uniformly. It is this intersection that turns the hazard of wind, storm surge and rain into a hurricane disaster. Inherent uncertainty associated with physical occurrence of storm and the magnitude of damage inflicted makes the system even more complex to understand (Katz, 2002). Increased development and population growth along the Atlantic coastline has been greatly responsible for increased economic losses from hurricanes (Pielke et al., 1998). Of course, socio-economic vulnerability of exposed regions is a major constituent of disaster risk and adds significant complexity to it. Cutter et al. (2003) propose various determinants of social vulnerability based on their power in explaining the variation in county level measure of vulnerability. These include socio-economic dependency (age, ethnicity and race), infrastructure vulnerability (density of built environment, housing stock and tenancy) and economic vulnerability (income, single sector economy and infrastructure dependency).[4] Davidson and Lambert (2001), define the Hurricane Disaster Risk Index (HDRI) as a composition of 4 major elements: (1) hazard; (2) exposure; (3) vulnerability; and (4) emergency response and recovery capacity. Additionally, it is increasingly recognized among researchers that the resilience of a region exposed to hazard relies heavily on their institutional qualities and strengths (Silbert and Useche, 2011). Accounting for all the factors mentioned, the impact of similar hazards in terms of intensity and strength happening with different special or temporal circumstances would have significantly different outcomes. One, particularly important aspect in a special-temporal dimension of disaster damages is clearly the adaptive capacity of the society. This can vary across locations, depending on a combination of the resilience levels and vulnerability (Dayton-Johnson, 2006).

Turning to the adaptation aspect of natural disasters, it is important to note that researchers make no clear distinction between adaptation and mitigation measures in reference to natural disasters. While the literature on adaptation to natural disasters is viewed in terms of coping and risk management strategies related to weather extremes such as floods, storms, droughts and other natural hazards (Burton, 1997), natural hazard mitigation is also defined in a similar fashion.[5] In the empirical literature we see a tendency to distinguish between hard and

[4] The spatial pattern in Social Vulnerability Index of the United States (SoVI) developed by authors suggests great vulnerability to environmental hazards of metropolitan counties in the east, south Texas and the Mississippi Delta region.

[5] For instance, Federal Emergency Management Agency (FEMA) defines natural hazard mitigation as *"any action taken to reduce or eliminate the long term risk to human life and property from natural hazards. This encompasses variety of actions from minor structural changes to an existing building that make it more resistant to the impacts of natural hazards (such as extra nails to hold roofing material in place during high*

soft adaptation measures. The former involve investment in dikes, seawalls and reinforcement of building codes, whereas the latter refers to early warning systems, land-use planning, insurance, foreign aid and support to small businesses (Hallegatte, 2009). Some group them into autonomous/reactive and planned/anticipatory measures (Mechler et al., 2010).[6] Fisher-Vanden et al. (2011) provide broader and perhaps most inclusive classes of adaptation in relation to the threat or onset of economic damage. Specifically, three types of adaptation measures are defined in terms of responses of the impacted sectors through the productivity shocks. Type I adaptation is referred to as passive, general equilibrium adjustments to damages that are possible because of price changes and substitution availability in the markets. Type II adaptation includes all protective and defensive measures that moderate impacts of onset due to the response in sectoral productivities. Type III adaptation measures include adaptive and responsive measures and are thought to reduce the extent of damage because the effectiveness of the productivity response could not moderate the direct impacts of environmental shocks.

In the risk and insurance literature, two types of alternatives to market insurance are commonly analyzed, these are self-insurance and self-protection. Self-insurance refers to all measures that affect the magnitude of loss, whereas self-protection serves to reduce the probability of loss (Ehrlich and Becker, 1972). This distinction, of course, is somewhat artificial because many preventative/defensive measures are found to reduce both the probability and the magnitude of loss. Marginal protectiveness of certain measures could also depend on the severity of natural hazards. This clearly suggests that these definitions should be used in relative terms. For instance, Lewis and Nickerson (1989) distinguish between "risk-reducing" and "risky expenditures" on self-insurance depending on their implications on loss magnitude. The former refers to all self-insurance measures for which marginal returns vary directly with the severity of a natural disaster, the latter is referenced when the marginal return on self-insurance and severity of hazard are inversely related.[7] Shogren and Crocker (1991) allow self-protection to influence both the probability and severity of undesired states of nature and show that increased risk exposure does not necessarily imply increased self-protection.

The opportunity to implement adaptive measures in advance certainly depends on the degree of event predictability. Highly uncertain events might limit the ex-ante adaptive resources especially if private agents exhibit myopic behavior (Smit et al., 2000). Informational asymmetry and uncertainty of natural hazard occurrence and its distributional impacts explain why the insurance market does not work properly in addressing issues of natural catastrophes. In addition to the long recognized phenomena of moral hazard and adverse selection, imperfections in the insurance market when dealing with disasters, also come from improper government interference. This leads to the issue of charity hazard. The term is defined in association with catastrophes and government intervention that offers post disaster relief and recovery assistance (Raschky and

winds) to major avoidance policies which permanently remove particularly hazardous areas from the development marketplace (such as public acquisition of hazardous sites)".

[6] The adaptation to the gradual change in the climatic environment is suggested to be primarily autonomous/reactive in nature; examples include changes in farming practices (private sector autonomous adaptation); beach nourishment and relief and reconstruction assistance (public sector autonomous/reactive adaption measures). In relation to the extreme events, such as climatic disasters, planned/anticipatory options of adaption are envisaged as more appropriate and effective measures. From the private sector's side this could include insurance, retrofit of housing, whereas public involvement would encompass improved building codes, spatial and regional planning, early warning systems and many others.
[7] Quiggin (1992) refers to them as "uncertainty-reducing" and "uncertainty-increasing" respectively in the analyses of health risk and self-protection decision.

Weck-Hannemann, 2007; Raschky and Schwindt, 2008). Paradoxically, without any guarantee of these charitable intentions ex-ante, but counting on experience of past relief programs and government involvements with catastrophes, the belief is created that financial assistance will be supplied if the disaster re-occurs (Coate, 1995). Ex-post provision of public relief entices individuals to put financial liability fully on the third party, creating the so called "Samaritan's Dilemma" (Buchanan, 1975). Kunreuther (2001) defines the syndrome of natural hazard when individuals exposed to disaster risk lack interest to protect themselves and property. This ignorant behavior consequently results in massive monetary losses, the financial burden of which is carried by society, government, insurance industry and other respective institutions. This heuristic attitude is attributed to ambiguity about the probability of the event reoccurrence, risk misperception, and bias.

Damages that natural hazards bring could be separated into two major categories: direct (stock) and indirect (flow) losses. The former refers to the loss in stock such as physical destruction of available productive capital, whereas the latter corresponds to a secondary loss triggered by these random shocks because disasters stall economic growth and disrupt business activities (Tatano et al., 2005). In addition to these direct losses there is an opportunity loss associated with the forgone economic growth, as long as the rest of the economy exhibits a positive growth pattern (Yokomatsu and Kobayashi, 2002), commonly deemed extremely challenging to quantify.

In this paper, we will address adaptation effects on direct impacts of hurricanes, represented by property losses. We synthesize highly intertwined components of disaster and similar to Davidson and Lambert (2001), define hurricane disaster risk as an intersection of four major constituents: (1) physical exposure, (2) economic exposure, (3) socio-economic vulnerability and (4) adaptation. First, it is the physical occurrence of a hurricane that causes damage. Perhaps, one could argue that repetitive occurrence of the same type of hazards (or others) paralyzes affected communities in terms of coping capacity. However, an important aspect in disaster history analysis is the length of time interval between recurrent processes. If disasters happen within a short period of time when communities are still coping and recovering from previous incident, the impact of an event would probably be catastrophic. The Japanese earthquake catastrophe in 2011 is a recent pertinent illustration of the importance of event sequence within a short period of time. The earthquake triggered the tsunami which later caused the nuclear disaster (non-natural, so called man-made disaster). Had these events happened independently at separate times, the impact might not have been so devastating. Similarly, consequences of hurricane Irene in 2011 on U.S. coastal regions, (in particular property damage), may not have been so severe if a preceding earthquake had not already damaged some physical infrastructure. Nonetheless, when time intervals between successive events are sufficiently long, historical exposure can in fact promote local adaptive behavior. There is a strong consensus among researchers of natural disasters that historical exposure to these hazards strengthens communities coping capacity. Often, they already have some mitigation measures in place implemented post previous disaster(s) and thus are better prepared for future events (Mileti, 1999; Sadowski and Sutter, 2008). The full extent of physical impacts of these shocks can only be comprehended by knowing the prevailing conditions (state) of the region exposed to such shocks and events preceding the hazard occurrence.

Second, to be able to approximate the extent of damages caused by a hurricane, as attempted in previous studies, it is imperative to know the economic exposure to natural hazards in terms of growing population trends, wealth accumulation, increases in built-up environment, etc. Third, the damage magnitude is determined by the vulnerability of the economy. It is the socio-economic conditions that transform a natural hazard into a disaster. Poor socio-economic conditions are most often connected to low grade buildings, housing and other infrastructure. If the prevailing socio-economic conditions are poor at the time disasters occur, even a less intense and less destructive hurricane could have devastating results and cause major loss in human life and property. Nonetheless, as much as people are concerned about natural hazards, they learn to live with them over time. The fourth element of disaster risk encompasses adaptation (structural and non-structural) and coping strategies of impacted communities. Knowing this, one can begin to understand the historical trends of hurricane impacts in terms of economic damages and the associated learning processes.

III. Conceptual Framework

In this section, we employ Lewis and Nickerson (1989) theoretical model to motivate discussion about features of different adaptation measures in relation to severity of natural hazard. The model characterizes the impact of hazard on property value under the limited financial liability of individual agents. Limited liability for loss happens because of the disaster relief program under which disaster victims receive compensations for their loss if the severe states of nature are realized.[8] Partial liability is modeled by bifurcating of the states of nature (benign vs. severe) under which each involved party (private vs. public sector) undertakes full responsibility for disaster protection and subsequent loss.

The individual is endowed with a certain level of exogenous wealth (W) and property which is exposed to risk. Individuals have to make a decision on self-insurance (adaptation) investment, denoted by x, to protect themselves against highly random natural shocks. z is defined as the random effect of natural hazard on an individual's property. Its distribution is governed by the cumulative distribution function, F(z) and is defined over the range $[\underline{z}, \overline{z}]$. Smaller values of z correspond to the severe states, whereas higher values of z define milder states of nature. The function D(x,z) measures the effect of environment on property value, after accounting for a self-insurance expenditure and a hazard level[9]. The properties of marginal return to self-insurance expenditure on property ($D_x(x,z)$) are not directly specified and depends on the interaction between x and the severity of the natural hazard, z. The function $D_{xz}(x,z)$ could, therefore, be negative or positive. If $D_{xz}(x,z) < 0$, we refer to such self-insurance measures as loss-reducing, whereas if $D_{xz}(x,z) > 0$, we call them loss-inducing[10]. In addition, it is assumed that if individual's property value falls below G, individual is qualified for public compensation. As such, individuals final wealth is bounded below by $(G + W)$ if severe states of nature are realized.

The function $D(x^*, z)$ is an optimal net property value and can alternatively be viewed as $\mathrm{D}(x^*, z) = 1 - L(x^*, z) - x^*$, if we assume that the initial property value is normalized to one, the price for a unit of self-insurance is unity and $L(x^*, z)$ denotes the realized property loss. x^*

[8] Schumacher and Strobl (2011) extend Lewis and Nickerson (1989) model by allowing not only uncertainty over the hazard impacts but risk over the states of nature to change. The predictions of the two models are essentially similar.
[9] $D(x,z)$is assumed to be twice-continuously differentiable in all arguments. Specifically, it is assumed that $D_x > 0$ and $D_{xx} < 0$ [9]. In addition, it is assumed that $D_z > 0$, which implies that the impact of a natural hazard on net property value is less, the milder the disaster.
[10] Lewis and Nickerson (1989) call them "Risk-Reducing expenditure" and "Risky Expenditure" respectively. Quiggin (1992) names them as "uncertainty-reducing" and "uncertainty-increasing".

represents the utility maximizing level of self-insurance expenditure[11] and is defined as a function of exogenous level of income, W and $F(z)$, cumulative density of the distribution of the severity of potential states of nature and minimum government compensation, G. Since our intention is to investigate the properties of $L(x^*, z)$ as it relates to wealth, self-insurance expenditure and hazard, it suffices to show that things that effect the function $D(x^*, z)$, have inverse implications on the properties of the loss function, $L(x^*, z)$. All else equal, higher values of $D(x^*, z)$, imply lower property losses, $L(x^*, z)$, whereas lower values of $D(x^*, z)$ translate into higher property losses. In the comparative static analysis (Table I on p. 215), the authors show that depending on the type of self-insurance (risky vs. risk-reducing), increase in the wealth level may or may not be followed by an increase of investment in protective measures. A similar non-linear relationship between disaster costs and wealth is also suggested by Schumacher and Strobl (2011). Higher degree of relative risk aversion is found to decrease self-insurance expenditure in benign state and increase it in the severe states of nature, whereas increase in degree of uncertainty has opposite implications. The more spread the risk, individuals tend to under invest in projects that are effective when severe states are realized and vice versa. Although direct implication of the self-insurance expenditure suggest reduction in property loss, depending on the severity of natural hazard, losses could either increase or decrease and the direction is governed by marginal effectiveness of protection (D_{xz}).

To what follows, we categorize and hypothesize effectiveness of certain measures relative to natural hazard, impacts endpoints, prevailing socio-economic conditions, and preceding physical events. Particularly, given that natural systems (hurricanes) cause two types of damages: direct (due to the impacts on physical capital and human lives) as well as indirect (disruption to economic and social systems) losses, we can define adaptation measures according to the impact endpoints as follow:

1) Measures that moderate the impact of natural system on the physical capital (buildings, roads, infrastructure, and productive capital);
2) Measures that moderate the impact of natural system on human life;
3) Measures that moderate impact of natural systems on the economic and social system.

The first is Type II adaptation measure of Fisher-Vanden et al. (2011), second measure is the Type I adaptation because through the reduced lethality (or injuries) of hurricanes we can infer general equilibrium, market based behavioral adjustment or private initiatives to protect their property from changing natural environment. The third measure is a Type III-like adaptation measure as it encompasses activities that potentially reduce rippling effect of direct losses that manifest themselves as indirect losses in the entire economy. Adopting these definitions we propose the following hypotheses:

1) Investment in Type III adaptation measures which include both adaptive (restricting development, relocation, and zoning) and responsive actions (immediate relief and clean-up activities) should exhibit loss-reducing and shock-smoothing effects respectively.
2) Type II adaptation measures are designated for major structural (dams, levees, shorelines stabilization) and infrastructural projects (rehabilitation roads, utilities and bridges) that have loss-reducing features, however their protective ability could be limited by designed

[11] $\max_x V = \max_x \left[U(G+W)F(\hat{z}) + \int_{\hat{z}}^{\bar{z}} U(D(x,z)+W)dF(z) \right]$ such that $D(x,\hat{z}) = G$; $V(\cdot)$ and $U(\cdot)$ denote expected utility and utility function, respectively, assumed to be strictly concave in *x*.

capacity of these structures. Once these thresholds are exceeded, one would expect losses to escalate. Also, provision of protective infrastructure could induce (reinforce) private investment, consequently resulting in increased wealth exposure to risk and thus higher losses. As such, it is not directly obvious whether these types of measures are loss-inducing or loss-reducing.

3) The effectiveness of Type I adaptation measures is also unclear because of uncertainty about behavioral adjustments of individuals to natural disasters or their reaction to public protective measures that could potentially alter their adaptive behavior. In our model, Type I adaptation measures include investment in mitigation planning, warning and awareness studies which have direct impact on human lives. Since we are interested in property losses, through the effect on human lives, we hope to recover mitigation efforts motivated by past exposure and investigate whether "safer hurricanes" are partially responsible for higher losses;
4) We conjecture that public provision of disaster mitigation and response measures, in general, exhibit a potential to distort private adaptation incentives and could be suggestive of promoting moral (charity) hazard.

IV. Estimation approach and data description

We analyze the implication of different adaptation and mitigation measures on hurricane-induced property losses for 864 counties in the North-Atlantic Basin region of the United States (Figure 4). These are counties that are located relatively close to the coastline and have experienced property losses from hurricanes at least once during the period studied, 1989-2009[12]. For some years we observe no property damage either because there were no major hurricane incidents or if there was one, it did not cause any property loss. Naturally, our sample contains large number of zeros for the dependent variable (property losses). This renders linear estimation methodology inappropriate, because we are interested not only in features of $E(y|x)$, but also in $P(y = 0|x)$. The Tobit estimation methodology seems most suitable to this particular problem (defined in the context of a "corner solution outcome", Wooldridge, 2002), because the dependent variable takes on the value of zero with positive probability but is a continuous variable over strictly positive values. The standard Pooled Tobit model for panel data is defined as

$$y_{it}^* = x_{it}\beta + u_{it}, \qquad u_{it}|x_{it} \sim N(0, \sigma^2), \qquad t = 1,2,\ldots,T \tag{1}$$

$$y = \max(0, y_{it}^*) = \max(0, x_{it}\beta + u_{it})$$

In a corner solution situation, the latent variable y_{it}^* is an artificial construct[13]. It is artificial because we observe zeros not due to the data censoring problem but rather because they are a natural (optimal in certain applications) outcome of an event (decision). Since zeros consist of large number of the dependent variable, we are interested in the features of $E(y_{it}|x_{it}, y_{it} > 0)$ and $E(y_{it}|x_{it})$.

[12] Including counties that have experienced property loss from hurricanes at least once during the period defined, we are able to analyze hurricane impacts not only for those counties that were directly hit, i.e. located on the observed hurricane tracks, but also for those that were exposed to hurricanes because of their proximity to the coast.

[13] Common application of the Tobit model is a situation when y^* is censored above or below some value because it is not observable for some part of the population.

To take account of potential heteroscedasticity and correlation of observations across time within each cross-sectional unit, we estimate the pooled tobit model using cluster-robust standard errors, allowing for within-county clustering of errors. Additionally, we control for county (μ_i) and year (λ_t) fixed effects.

$$\begin{aligned}
&\frac{Loss_{i,t}}{Pop_{i,t}} = \beta_0 + \beta_1 ln\left(\frac{Inc_{i,t}}{Pop_{i,t}}\right) + \beta_2 \left[ln\left(\frac{Inc_{i,t}}{Pop_{i,t}}\right)\right]^2 + \beta_3 \Delta Pop_{i,t-1} + \\
&\beta_4 \Delta Bus.Est_{i,t-1} + \beta_5 \frac{Unemp_{i,t}}{Pop_{i,t}} + \\
&\beta_6 \frac{Vul.Inf_{i,t}}{Pop_{i,t}} + \beta_7 Hur_{i,t} + \beta_8\left(\textstyle\sum_{t_0}^{t-1} Hur_{i,t}\right) + \beta_9 MH_{i,t} + \\
&\beta_{10} Dis_{i,t-1} + \beta_{11}(dc * ts_{i,t}) + \beta_{12} ln\left(\textstyle\sum_{t_0}^{t-2}\left[\frac{Tipe\ I_{i,t}}{Pop_{i,t}}\right]\right) + \\
&\beta_{13} ln\left(\textstyle\sum_{t_0}^{t-2}\left[\frac{Tipe\ II_{i,t}}{Pop_{i,t}}\right]\right) + \beta_{14} ln\left(\textstyle\sum_{t_0}^{t-2}\left[\frac{Tipe\ III_{i,t}}{Pop_{i,t}}\right]\right) \\
&+ \beta_{15} ln\left(\textstyle\sum_{t_0}^{t-2}\left[\frac{BC\ \&\ Des_{i,t}}{Pop_{i,t}}\right]\right) + \beta_{16} BCEGS_{i,t} + \beta_{17}(CRS_{i,t}) + \\
&\mu_i + \lambda_t + \varepsilon_{i,t}
\end{aligned} \tag{2}$$

All variables given in the value terms (property loss, income, Type I, Type II and Type III adaptation, building codes and design studies) are converted to 2005 real prices using GDP deflator. County level property loss estimates from hurricane incidents are obtained from the SHELDUS (Spatial Hazard Events and Losses Database for the United States) database. Other explanatory variables are based on estimates from the US Census Bureau, Bureau of Economic Analysis (BEA) of US Department of Commerce, U.S. Bureau of Labor Statistics, National Oceanic and Atmospheric Association (NOAA), Federal Emergency Management Agency (FEMA), Insurance Services Office (ISO), and International Code Council (ICC). The explanatory variables of the model are grouped into four broader categories, defined below, based on their respective roles in explaining property loss: (1) physical exposure/physical vulnerability; (2) economic exposure; (3) socio-economic and infrastructure vulnerability; and (4) adaptation, coping and recovery.

Dependent variable:

Per capita Property loss, $\left[\frac{Loss_{i,t}}{Pop_{i,t}}\right]$: is defined as per capita total annual observed property loss in US dollars from all hurricanes that a county experienced within a given year. According to the SHELDUS, estimates are derived from several sources including, the National Climatic Data Center, the National Geophysical Data Center and the Storm Prediction Center. One of the obvious limitations of these data is that it equally divides observed damage estimates for specific hazards between affected counties. To account for county level variation in property losses, we developed weights using Emanuel's (2005) proposed wind speed and economic loss relationship, the so called power dissipation index (PDI) given by:

$$PDI = \int_0^{\tau} V_{max}^3 dt$$

V_{max} is the maximum sustained wind speed by a county and τ is the period of hurricane persistence (season). Under the assumption that $PDI \approx Economic\ Damage$, using the NOAA best hurricane track observations, for every observed point on a hurricane track starting at its origination, defined by the longitude and latitude, we calculated wind speeds by county using Willoughby-Darling-Rahn[14] (2006) parametric wind distribution model. These individual wind speeds were cubed and summed over the entire hurricane season for each individual county. We then calculated total of the PDI using the formula: $\sum_{i=1}^{N} \int_0^{\tau} V_{max_i}^3 dt$, where $i = \{1, \ldots, N\}$ and N is the total number of affected counties that SHELDUS uses to derive equal county level damage estimates from individual incidents. Correspondingly, weights (w_i) were generated using the simple share rule $w_i = \frac{\int_0^{\tau} V_{max_i}^3 dt}{\sum_{j=1}^{N} \int_0^{\tau} V_{max_j}^3 dt}$ which were further applied to county level damage estimates recorded by SHELDUS to generate individual county level variations.

Physical exposure/physical vulnerability:

Count of hurricanes, cat.1-5 $[Hur_{i,t}]$: is the total annual count of hurricane incidents of all categories based on the NOAA best track observations that made landfall in a specific county. These counts include only those counties that were directly hit by a specific hurricane i.e. located on a hurricane track. To obtain this variable, we used ArcGis software to intersect hurricane tracks with US county map. In the sample, we have 880 incidents of counties being directly hit by one hurricane in a year, 42 incidents of counties being hit by two named hurricanes, and only one county was hit by three hurricanes.

Lag of cumulative count of hurricanes, cat. 1-5 $[\sum_{t_0}^{t-1} Hur_{i,t}]$: is the rolling cumulative sum of annual hurricane counts that made landfall on the US coast from 1853 onward and is used in its lagged value. Historically, Monroe County, Florida in our sample has been hit maximum number of 39 hurricanes since 1853.

Major hurricane $[MH_{i,t}]$: is a indicator variable if a county was directly hit by a major hurricane defined as category 3 or higher in a given year. We encounter 512 incidents of major hurricane hits in our sample.

All three of these variables accounting for current as well as historical incident of hurricanes are assumed to proxy physical vulnerability. Counties with current exposure of all categories of hurricanes are expected to suffer with higher property losses. The impact is likely to be severe for those counties that were hit by a major hurricane. As for the effect of historical exposure on property losses, the direction is not clear: it could be negative or positive. If negative it would potentially capture passive adaptive responses through past experience, whereas if positive, it could either indicate a "*curse of nature (wrath of God)"* (Kahn, 2005; Raddatz, 2009)

[14] Dual exponential profile for the parametric wind distribution model is of the following form:

$$V(r) = V_{max}\left[(1-\mathrm{A})\exp\left(-\frac{r-R_{max}}{X_1}\right) + A\exp\left(-\frac{r-R_{max}}{X_2}\right)\right], \quad R_1 \le r$$

where V_{max} is the maximum wind speed; R_{max} is the radius of maximum winds along a radial; X_1, X_2, A and R_1 are parametrically derived from primary characteristics of the wind (V_{max} and R_{max}). See equations (7a)-(7c) (p. 1108) and (10a) – (10c) (p. 1113) in Willoughby et al. (2006)

because of the physical location or "*lulling effect*". The latter as suggested happens as a result of insufficient provision of protection from hazards by individuals and public sector. In particular, individuals (local government) tend to lull into a "false sense of security" if previous disasters were not as bad as expected (Sadowski and Sutter, 2008).

Lag of other disasters, declared by the President $\left[Dis_{i,t-1}\right]$: is the annual count of other disasters by county that were declared by the U.S. president. It includes all types of natural and manmade disasters, reported by FEMA. The variable is lagged by one period to account for its importance in the sequence of geophysical processes. The sign of this variable is ambiguous. On the one hand, we expect counties experiencing any other types of disaster in the previous period to be more vulnerable and less capable to cope with the impact of a hurricane. However, on the other hand, accounting for immediate response/relief assistance and clean-up activities, the impact of past disaster relief programs could have a mitigating effect on future losses.

Coastal county * tropical storms $\left[dc * ts_{i,t}\right]$: is an interaction term of a dummy variable, that equals to one if a county has a coastline and zero otherwise, and the total number of tropical storms (cyclones, tropical depressions and all categories of hurricanes) that made landfall in a county in a given year. According to NOAA, coastal counties are defined according to one of the following two criteria: 1) at least 15 percent of a county's total land area is located within the Nation's coastal watershed; or 2) a portion of or an entire county accounts for at least 15 percent of a coastal cataloging unit. 45.60% of our sample counties are defined as coastal. All else held constant, these counties are expected to experience higher property losses as compared to their inland counterparts.

Economic exposure:

Per capita income $\left[ln\left(\frac{Inc_{i,t}}{Pop_{i,t}}\right)\right]$: Personal income estimates are obtained from the Bureau of the Economic Analysis, US Department of Commerce, available from 1969 to 2009. According to the BEA definition *"Personal income is the sum of net earnings by place of residence, rental income of persons, personal dividend income, personal interest income, and personal current transfer receipts."* This variable is a proxy for the county's wealth exposure to natural hazards. To account for possible non-linear relationship between property loss and income, we additionally include its squared term. Higher economic exposure implied by an increase in wealth level could potentially exacerbate damage, however more and more wealth also suggests more resources to invest in improved infrastructure and thus should have a loss mitigating effect.

Lag of Population Change $\left[\Delta Pop_{i,t-1}\right]$: is the lagged value of population change by county based on the BEA population estimates.

Lag of Business Establishment Change $\left[\Delta Bus.Est_{i,t-1}\right]$: is the lagged value of the change in the total number of business establishments (all types) by county based on the U.S. Census Community Business Patterns database. Controlling for the growths in population and business establishments, along with the level of income, our model fully accounts for growing economic exposure as a primary driver for an increased property loss.

Socio-economic and Infrastructure Vulnerability:

Per capita vulnerable housing $\left[\frac{Vul.Inf_{i,t}}{Pop_{i,t}}\right]$: It is a vulnerable housing stock per capita measured as total number of mobile homes and housing units built before 1940 and are based on the US census decennial data. The missing years between the decades were linearly interpolated. The variable captures the vintage and physical vulnerability of the built infrastructure. Higher values of the variable translate into higher infrastructure vulnerability and thus are expected to result in higher property losses.

Unemployment rate $\left[\frac{Unemp_{i,t}}{Pop_{i,t}}\right]$: is defined as a share of unemployed people in the county's total population. The variable is obtained from the U.S. Bureau of Labor Statistics. Clearly there are many more choices that could serve as potential candidates for the socio-economic vulnerability of an exposed geographic area, such as poverty level, social dependency rate defined by age, gender or ethnic composition, etc. However, our preference for an unemployment rate is primarily governed by its ability to capture lack of financial resources and limited economic activities. More unemployed population in a county, all else held constant, implies fewer resources to self-protect and insure against natural hazard. As such we expect counties with higher unemployment rate to suffer with higher property losses.

Adaptation, Coping and Recovery:

To control for private and public provision of adaptive resources, we consider several adaptation and mitigation measures. We consider both horizontal (Type I, Type II, Type III, building codes) and vertical dimensions (local vs. federal) of protective measures. The data comes from Federal Emergency Management Agency (FEMA) and are based on the Hazard Public Assistance and Hazard Mitigation Grants Programs. Both programs were established under Robert T. Stafford Disaster Relief and Emergency assistance Act that was passed in 1988. The hazard mitigation grants are available from 1989, whereas public assistance grants data covers projects from 1998. According to FEMA, the Public Assistance Grant Program is provided to assist state, tribal and local governments and certain types of private non-profit organizations to quickly respond and recover from major disasters or emergencies declared by the president. Even though public assistance grants are available as immediate response to disaster-effected communities, the program also encourages protection from future damages by providing hazard mitigation measures during the recovery process. On the other hand, the Hazard Mitigation Grant Program serves primarily long-term mitigation purposes. To streamline the delivery of the mitigation grants FEMA encourages states to develop coordinated mitigation management and planning program before disaster strikes. While mitigation grants are granted after a major disaster declaration, by encouraging mitigation planning and management during the pre-disaster period, the program coordinates both pre-disaster and post-disaster actions and is aimed to eliminate long-term risk to property and human life from natural hazards.

The FEMA data is reported by hazard incident for all declared disasters by county. Certain projects in the database were approved to provide statewide coverage; however, since we cannot identify specific amounts given to a county within a state, we disregard these statewide covered projects. As such, our data includes only those projects that were identified by a county name and were designated to protect and mitigate losses from disaster types such as hurricanes, floods or coastal storms. Appropriateness for public provision of adaptive measures proxied by FEMA variables could perhaps be criticized for several reasons. Some researchers have found evidence of political motivation in the disaster declaration and consequent allocation of hazard mitigation and public assistance resources by FEMA. Garrett and Sobel (2003) argue that the political bias is twofold: on the one hand bias is generated from the process of disaster declaration - the law grants the president sole discretion to declare disasters in the United States using no concrete sets of criteria; on the other hand, congressional oversight of FEMA expenditures and members of respective committees could have an important influence on resource allocation.

One important aspect to note is that federal funds are somehow tied to the level of damages inflicted by disasters, even though the size of mitigation grants are not necessarily dictated by the damage level as they aim for long term protection solution. As a result, one would expect unobservable factors that determine property losses to be related to the processes that generate types of adaptation measures in our analysis. Inclusion of the contemporaneous mitigation or public assistance variable in the estimable model therefore could create a potential source for endogeneity bias based on the simultaneity of the dependent variable and the size of federal funds. To safeguard against the bias inference we correct for this potential endogeneity by including 2-year lagged value of the rolling cumulative sum of all types of adaptation measures. Alternatively, we also consider 1-year lagged differences in public adaptation investment to investigate whether an inclusion of stock vs. flow investment would have significantly different implications in terms of mitigating property loss. These measures do not entirely correct for endigeneity bias. One would still argue, that areas with the most protective measures are those that have had most damages historically and that's the reason we see protective measures in those places in the first place. Despite these limitations, we believe they still provide good, not ideal solution to address the endogeniety problem presented in the paper. Also, prior evidence about political bias and congressional preferences in allocating federal funds between affected states and regions give us additional safeguard against potential biased inferences. Note that adaption variables are provided in per capita log terms. Detailed description of each type of measures follows.

Type I adaptation: $\left[ln\left(\sum_{t_0}^{t-2}\left[\frac{Type\ I_{i,t}}{Pop_{i,t}}\right]\right)\right]$: covers federal grants to communities for hazard mitigation planning and hazard identification purposes. In particular, under these types of programs, localities are obliged to develop comprehensive mitigation strategy for reducing risks to life and property. In addition, this variable includes the FEMA mitigation grant category designated for implementing improved warning systems (defined in the database as "a component of planned, adopted and exercised risk reduction plan").[15]

Type II adaptation: $\left[ln\left(\sum_{t_0}^{t-2}\left[\frac{Type\ II_{i,t}}{Pop_{i,t}}\right]\right)\right]$: these types of grant activities primarily target vegetation management that serves as natural protective measure from hazards, shoreline and land slide stabilization activities. It also includes water and sewer protection, infrastructure rehabilitation projects (bridges, roads), storm water management and utility protection measures as well as rehabilitation of parks and recreational facilities, including playgrounds, pools, mass transit facilities, beaches and cemeteries. In addition, Type II adaptation measures include those

[15] Type I activities correspond to 90 , 600, 700, 800 level activities defined in the Hazard Mitigation Projects database provided by FEMA . http://explore.data.gov/Other/FEMA-Hazard-Mitigation-Program-Summary/wsf8-txi9

federal grants that are given to localities for major structural projects such as construction and rehabilitation of dams, levees and flood control structures. [16]

Type III adaptation: $\left[ln\left(\sum_{t_0}^{t-2}\left[\frac{Type\ III_{i,t}}{Pop_{i,t}}\right]\right)\right]$: covers immediate response grants defined as "Measures taken before, during and after a disaster to eliminate/reduce an immediate threat to life, public health, or safety, or to eliminate/reduce an immediate threat of significant damage to improved public and private property through cost-effective measures" and includes funds allocated for clean-up activities such as debris removal, removal of certain building wreckage, damaged/destroyed building contents and other disaster-related material deposited on public and, in very limited cases, private property. This type of adaptation category also encompasses hazard mitigation funds designated for acquisition of private property and land (structures and land), elevation of private and public structure. Moreover, it includes non-structural retrofitting and rehabilitation, as well as the relocation of private structure[17].

Building Codes and Designs: $\left[ln\left(\sum_{t_0}^{t-2}\left[\frac{BC*Des_{i,t}}{Pop_{i,t}}\right]\right)\right]$: includes federal grants given for activities that serve feasibility engineering and design studies; development, implementation and enforcement of codes, standards, ordinances and regulations and others.[18]This variable serves as a proxy for improved building codes, engineering designs, standards and regulation enforcement.[19]

CRS total credit points [$CRS_{i,t}$]: data on private and local level adaptation measures are nonexistence. To account for some of the important mitigation strategies implemented by localities we consider Community Rating System (CRS) total credit points. CRS is a voluntary program designed under the auspices of the National Flood Insurance Program (NFIP) to incentivize participating communities to develop a protective and flood resistant environment beyond basic requirements mandated under the NFIP. The incentives are provided in the form of discounts in flood insurance rates. Specifically CRS evaluates and classifies communities into 10 classes rating 1-10: class grade 10 refers to 'no discount', whereas class 1 implies discounts as high as 45%. The classifications are granted for accrued credit points for various creditable activities defined by the program. Every year communities are required to recertify or re-verify

[16] Type II covers 300, 400, 500 level activities defined in the Hazard Mitigation Projects database provided by FEMA . http://explore.data.gov/Other/FEMA-Hazard-Mitigation-Program-Summary/wsf8-txi9,

[17] Type III covers 200 level activities defined in the Hazard Mitigation Projects database provided by FEMA http://explore.data.gov/Other/FEMA-Hazard-Mitigation-Program-Summary/wsf8-txi9, as well as Category A and B of Emergency Work of FEMA Public Assistance Program and C, D,E,F and G categories of Permanent Work of FEMA Public Assistance Program (Public Assistance Policy Digest; p. 17, 2008).

[18] Activities correspond to 100 level activities defined in the Hazard Mitigation Projects database provided by FEMA . http://explore.data.gov/Other/FEMA-Hazard-Mitigation-Program-Summary/wsf8-txi9

[19] According to the International Code Council (ICC) in recent years all 50 states have adopted the unified I-Codes at a State or Jurisdictional level. The list of codes includes International Building Code (IBC), International Residential Code (IRC), International Fire Code (IFC), Energy Conservation, Plumbing, mechanical codes and many others. However the adoption at the state level does not necessarily imply an adoption at the local level. As of 07-15-2011, ICC reports about 3.7% of our sample counties have adopted international codes county-wide. Unfortunately we could not include this information in the model due to identification problem restricted by fixed effects estimation. Code adoption list of ICC gives information about the codes by the year of edition, however it does not provide information of the actual year of code adoption and enforcement E.g. Jurisdictions reported with 2009 edition of building codes could have adopted 2009 edition in the same year or later. Another limitation of ICC report is that not all jurisdictions notify ICC of code adoptions which suggest that code adoption rate of our sample counties could be higher than 3.7% reported. http://www.iccsafe.org/gr/Documents/jurisdictionadoptions.pdf

that they continue to perform activities that have been credited by the CRS. If a community is not properly or fully implementing credited activities, its credit points, and possibly its CRS classification, will be revised. Our preference for CRS program over NFIP participation was primarily governed by the fact that CRS is inclusive of NFIP minimum standard requirements including the "100-year flood" or base flood elevations. Additionally, CRS program provides fully informed and quantifiable tool about adaptation/mitigation activities that are pursued by local authorities to attenuate flood related losses and hazard. Maintaining or upgrading class schedule guarantees that communities are in compliance with certain regulation and moreover, remain committed to continue implementing these policies. These credit points serve an ideal indicator for a local level up-to-date adaptation measures (Brody et al., 2009c). More points imply more hazard resistant built environment and is expected to reduce property losses.

BCEGS [$BCEGS_{i,t}$]: Although mandating building codes is an important loss mitigation strategy, code mandates at the community level does not necessarily guarantee its effective enforcement (Insurance Services Office, ISO). ISO has developed a grading system referred as BCEGS (Building Codes Effectiveness Grading System) that allows evaluation of building code performance with an emphasis on mitigation from natural hazards. The grading serves the needs of the insurance industries in terms of insurance rating and underwriting. The BCEGS grading is from 10 to 1, in descending order, 10 indicates the worst performance of the code enforcement and 1 refers to *"exemplary commitment"*. Although public data allow one to look at distribution of counties by BCEGS grades (see Figure 6), does not permit to identify BCEGS grades by individual counties. To capture the effectiveness of code enforcement, we approximate BCEGS by using a dummy variable to identify whether in a given year a county was classified as the CRS class 7 or lower. CRS participating communities should adhere to certain pre-requisites in order to advance to certain classes especially those at lower scale (class 7 or lower, class 4 or lower and class 1). For example, class 7 or lower requires communities to have a classification of 6 or lower in the Building Code Effectiveness Grading Schedule (BCEGS) of Insurance Services Office. We expect counties classified as CRS class 7 or lower to experience less property loss because they have relatively better enforced building codes and more mitigation measures in place. Summary statistics of all variables considered in the empirical study is provided in appendix (see Table 1).

V. Results and Discussions

In tables 2, 3 and 4 we present estimation results of the model; estimated coefficients and conditional and unconditional marginal effects for each explanatory variable. Our results are consistent with the proposed hypothesis that higher physical exposure, economic exposure and socio-economic and infrastructure vulnerability are major drivers for property loss. We find a non-linear relationship between economic exposure and property loss. Positive coefficient associated with the per capita income implies that more wealth initially translates into higher property loss. Per capita average income elasticity of loss is found to be around 8%. However, greater wealth results in less property loss as captured by the negative coefficient associated with the squared income. The income level in per capita log terms where we see loss mitigating effect of wealth is around 10.67 US dollars. Only 67 counties in our sample have per capita income higher than this threshold level, 64 of which are coastal counties. Negative sign of the squared term could potentially suggest that wealthier economies have more resources to invest in protection and improved engineering standards to withstand severe hurricanes. This finding is in line with Kellenberg and Mobarak (2008) findings of nonlinear relationship between damages and GDP. This is suggested by a tradeoff between consumption and demand for risk reduction measures at different wealth level. Particularly, likely preference for consumption is suggested at a low income level, whereas preference for investment in mitigation measures at higher levels of income. Schumacher and Strobl (2011) also propose an inverted U-shaped and U-shaped relationship between wealth and economic losses for countries depending on their experience with hazard levels. They argue that countries with low-hazard index initially incur higher loss which subsequently becomes less as income increases and vice versa for high-hazard countries.

Although smaller in magnitude, the evidence of economic exposure being a primary driver for increased property loss is also seen by the positive and significant coefficients associated with population and business establishment changes, respectively. Our finding is consistent with a cautionary note of Pielke et al. (2008) about potential threat associated with the growing concentration of population, property and wealth along the coastlines. As expected, we find positive and significant coefficients associated with the unemployment rate and the vulnerable housing stock, suggesting that economic and infrastructure vulnerability exacerbate property losses. Specifically, results indicate that a one percent increase in unemployment rate translates into 0.05% percent increase in per capita property loss. Less economic development, represented by high unemployment rate, is indicative of less financial resources to protect and cope with natural hazards. Poorly built environment also contributes to higher damages. A 1% increase in per capita vulnerable housing stock is responsible, on average, for additional 0.14% increase in per capita property losses. These findings are in line with the social vulnerability literature of natural disasters (Cutter et al., 2003). The fact that our sample is not restricted to those counties that were directly hit by hurricanes, suggests that when controlling for other factors, vulnerability of the county is not only determined by the intensity of hurricanes but rather is a function of socio-economic conditions as well. Poor socio-economic conditions clearly suggest transformation a hazard incident into a natural disaster is likely.

Geography and physical exposure as expected also matters. Coefficient associated with contemporaneous hurricane incidents is statistically significant and positive. Counties experiencing repetitive occurrence of all categories of hurricanes in a given year are more vulnerable to hazards than those experiencing them infrequently. If a county is directly hit by a hurricane, of any category, it incurs $137.39 higher per capita loss in real terms compared to a year without direct hurricane hits. Correspondingly if it was hit twice, repetitively, losses would increase by $175, whereas three hurricanes in a year, maximum number of hits observed in our sample, escalates per capita losses to as high as $227.80 We find that per capita losses are $62.67 greater for counties that were hit by one major hurricane in a given year as compared to a case of less intense or no hurricane incident at all. Given the sample population average of 125,970 per county, $62.67 per capita term for major hurricane hit implies 7.8 million dollars of additional property loss per average county. We also find that coastal counties that experience frequent occurrence of all types of tropical storms (tropical depressions, tropical cyclones and all categories of hurricanes) on average suffer $22.5 per capita higher losses than their inland counterparts, which is equivalent to an additional 2.8 million dollars of total property loss per average coastal county.

Regardless of the direction of these results, we are not particularly in favor of labeling physical exposure as the “curse” or “wrath” of nature brought by a geographic location. It is well recognized by natural disaster scientists that disasters are the act of human beings and the root of the problem lies not as much in unpredictability of natural events as in interaction of natural system with socio-economic and the constructed environment. As noted in Mileti (1999) “human beings, not nature, are the cause of disaster losses”. Furthermore, if this truly indicated a curse of nature, we would have found some evidence of increased losses from previous exposure as well. Instead what results show is that communities historically exposed to hurricane hazard are more resilient to and experience less damage. The negative and significant coefficient associated with entire past hurricane incidents could possibly suggest some effects of private, market based adaptation actions motivated through prior exposure. Average reduction in total property loss in a county experiencing prior hurricanes, is around $209,899. The results are consistent with findings by Sadowki and Sutter (2008) in which authors also argue that counties directly affected by a hurricane at least 10 years prior to a current incident have significant reduction in loss. Interestingly, a county, where other types of disasters were declared by the president one year prior, incurs on average $1.7 million less property loss from hurricane incident in the following year. One possible explanation of this sign could be the impact of after-shock relief and assistance activities and suggests the importance of timely response in strengthening overall economic resilience of impacted communities.

Controlling for economic, physical, socio- and infrastructure vulnerability, we are better able to isolate the impacts of various types of adaptation and coping measures defined in our study. Specifically, results suggest that adaptation measures funded through FEMA hazard mitigation and public assistance projects entailing building codes, regulations and engineering designs significantly reduce property loss. This is represented by the negative coefficient associated with “building codes and engineering designs” variable. All else equal, a 1% increase in total cumulative investment in enforcement of building codes, standards and regulatory measures are responsible for 0.023 percentage point reduction in per capita property losses. The results are important and consistent with the findings by Burby (2005) on the importance of a state’s role in mandating comprehensive plans and building codes at a local level. Our results reaffirm significant loss-reducing benefits of public policy strategy that require more stringent regulation and enforcement measures at the local level. However, as Burby (2005) notes state level adoption of mandates is very slow and by a great deal, are still “*underutilized”.* Perhaps, more attention should be paid by the federal government or other advocates to spur coordination between state and local level planning especially when environmental hazard is a concern. Additionally, we also find that the effectiveness of code enforcement is another important aspect of building code adoption and significantly reduces property loss. A county that is classified as CRS class Category 7 or lower suffers on average $2.02 million less property loss in a given year and this is attributed to effective code enforcement. Failure to adhere to regulatory standards and poor enforcement performance could be as bad as no adoption. One of the significant conclusions drawn from this finding is that reevaluation and improvement of codes, regulation and law performances seem to be promising sustainable disaster mitigation strategy.

We find that local level adaptation is an important loss mitigation strategy. Specifically, local initiatives to adapt beyond minimum safety requirements mandated by the National Flood Insurance Program is found to lower property losses as shown by the negative and significant coefficient associated with the “CRS total credit points” variable. Activities worth 500 credit points, sufficient to transit a county to a better CRS classification, imply on average $1.6 million property loss saving. Loss-mitigating effects of CRS scores on flood-induced property loss were also found by Brody et al. (2007) and our results further reaffirm previous findings. One thing to note about the CRS program is that the participation rate in CRS, even though premium discounts make the program more attractive than any regular voluntary program, is very low. As of 2011 there are 1164 communities at different jurisdiction level (municipality, city, borough and county) that receive premium discounts. Encouraging participation and promoting community's transition through CRS classes clearly pays-off in terms of reducing property loss. Another important aspect of CRS credit points is that these credits earned are heavily weighted towards non-structural projects such as raising public awareness about hazard, feasibility studies and hazard identification. Significance of this finding is immense given the recent shift of climate policy agenda towards sustainable disaster mitigation direction with particular emphasis on local level adaptation efforts and their linkage with external risk mitigation options (IPCC, 2012).What these results essentially indicate is that localities that take partial (or full) responsibilities for potential damages posed by natural hazards are more resilient. Being less dependent on external assistance and be able to cope with consequences of natural disasters using one's own resources, as suggested in prior studies, fosters and promotes a desirable, sustainable hazard mitigation approach (Mileti, 1999). Since Community Rating System is an incentive based mechanism, designing different incentivized systems to promote local interests to provide hazard protection is another important policy implication of these results.

Adaptive and coping activities defined under Type III measures also exhibit loss reducing features. Specifically we find that a one percent increase in total historical investment on these types of measures on average results in 0.004 percentage points reduction in per capita property loss. Adaptive part of these measures includes restricting development through relocation of private structures and acquisition of private property/land as well as retrofitting and elevation. On the coping/responsive side we have immediate response grants aimed to alleviating loss of life and property as well as projects that entail clean-up activities after major disasters. Two potential suggestions seem plausible from this finding. One, it suggests that emergency projects are extremely effective tools in reducing aftermath of disaster shocks. Second, results are indicative that *where to build* is a significant loss mitigation strategy. This further signifies that loss mitigating strategies entailing the aspect of "how to build" (building codes and their effective enforcement, retrofitting) could be complemented by strategies that concern "where to build" (zoning, relocation, restricting development) aspect of disaster preparedness.

Additionally, we find some market-based or so called "passive adaptation" measures to indicate significant reduction in property losses. This is seen by the negative and significant sign of the Type I adaptation variable, which captures mitigation planning, hazard identification, awareness studies and improved warning systems. The results indicate that a one percent increase in federal investment in Type I measures translates into reduction in property loss by 0.023%. Given the definition of a variable, although we are not able to account for the full impact of "warning systems" on property losses, because these systems are commonly implemented at the state level and their provision is somewhat unified across counties, the results still indicate that projects that aim to improve local warning and mitigation planning measures[20] are important loss mitigation strategies. Loss mitigating effects of Type I adaptation measures contradicts with Sadowski and Sutter (2005) argument that "safer hurricanes" or "less lethality" contributes to more property losses. On the contrary, we show that not only hurricanes become "less lethal" because of improved planning and warning system but they also mitigate property loss and as such these measures make hurricanes safer in all regards. At the onset, it may seem

[20] E.g. the project defined under the project type "600.1: Warning Systems (as a Component of a Planned, Adopted, and Exercised Risk Reduction Plan)" on a county level could entail automated enhancements to existing warning systems or it could include flood warning systems (survey building elevations; update area maps with survey information; purchase computer hardware and software and establish data base with survey information - develop warning procedures to be implemented by city and educate community).

less intuitive to argue that improved planning, awareness studies and warning systems actually reduce property losses, because these systems do not have direct impact on physical property. However, information communicated via these education and warning systems seem to effect individuals' perception of risk and alter their behavior to self-insure. Our finding clearly provides some direction for the debate among researchers about the economic benefits of hurricane planning and warning systems vs. economic benefits of an alternative public policy option such as investment in protective infrastructure. The focal argument of Letson at al. (2007) is that the quality of forecast does not have a direct, one to one correspondence with the quality of forecast communication and subsequent response. Even though we are not able to assess full net benefits of improved warning systems (cost of warning system vs. benefits, captured by potential hazard-loss reduction effects: reduced evacuation costs, reduced property damages, reduced risk exposure, reduced health risk and many others), results show that investment in improved planning and warning systems clearly pays off, at least partially in providing increased incentives for individuals to protect property from natural hazards and as such represents a promising disaster mitigation public policy strategy.

We find evidence that public investment in major structural projects defined as Type II adaptation measures exhibit loss inducing features suggested by a significant and positive coefficient associated with this variable. These measures include investment projects to restore utilities, public buildings and equipment, to construct and maintain dams and levees, flood control projects, finance land slide and shoreline stabilization activities. Furthermore, Type II also incorporates an investment in public infrastructure projects, such as rehabilitation of roads, bridges, water and sewer protections, as well as utility protective measures. A percent increase in average per capita property loss in response to a one percent increase of Type II investment is around 0.0126%. There are three potential factors that could potentially govern the positive sign for these types of investments. First, providing protective infrastructure could induce development, if the private sector responds positively to such types of government expenditure. If this occurs, we end up with more wealth exposed to risk. Kousky et al. (2006) using a theoretical framework argue that private investors respond positively to public protection by investing more in private capital and that the causation runs in opposite direction when the public sector protects in response to increased private investment. Second, investment in structural and infrastructural projects themselves adds value to increased resources at risk and could amplify physical damage, especially if we consider their protective capacity limits. Silbert and Useche (2011) use an investment in infrastructure as a proxy for increased resources at risk and find that such types of investments increase small island economic vulnerability to natural disasters. Our results conceivably support previous findings and proposed hypothesis. Third, possible explanation for a positive sign could be suggestive of some evidence of moral (charity) hazard. The public provision of protection could potentially distort private incentives to self-protect. Higher heuristic attitude of individuals exposed to risk, lack of responsibility for disaster losses could consequently be responsible for a huge financial burden on the public sector. Cohen and Werker (2008), Raschky and Weck-Hannemann (2007), Raschly and Schwindt (2008) show that free disaster relief in the context of international aid creates perverse incentives on governments receiving aid to provide sufficient protection from disasters. Lewis and Nickerson (1989) also demonstrate that when governments "exhibit a commitment to compensate disaster victims", individuals behavior to self-protect changes. This creates a huge divergence between the socially optimal level of self-protection from the government's point of view and an optimal level of protection that is utility maximizing.

Another interesting finding is that when instead of cumulative investment we consider 1 year-lagged differences in all types of adaptation measures, we see that these measures individually have significant loss mitigating effects. Perhaps, this could be an indication that cumulative historical investment in major structural projects allows sufficient time period to see some behavioral adjustments (more economic exposure in vulnerable areas). It could be that building these structural projects promotes so called "levee effect" and creates a fall sense of security leading to even higher exposure and thus higher losses when unexpected natural events happen. These types of behavioral adjustments, however, seem not to be possible in the short term and the case is supported by loss reducing effects of only one year's additional expenditures on protective measures. The signs and significance of all regression coefficients remain consistent when both cumulative and additional adaptation expenditures are included in the regression, further supporting our findings. Acknowledging the potential problem of endogeneity and limited power of instruments (cumulative lags) used in the study, we are particularly cautious of making conclusive statement about loss inducing features of these types of structural and infrastructural projects. Nonetheless, given the robustness in the estimates under different model specifications[21] could be suggestive of evidence of moral hazard (see Tables 5, 6, 7 and 8). Needless to say, further research in this direction is needed in order to make conclusive arguments.

Due to the nature of devastating catastrophes and their consequences, oftentimes it seems politically and morally infeasible for a government not to help disaster victims or not provide protection in areas exposed to hazard. Our results do not necessarily discourage implementation of loss mitigation measures by federal government. On the contrary, we show that all projects implemented historically through FEMA that focus on regulations, zoning, relocation, awareness studies, improved warning systems and retrofitting have substantial loss-reduction effect. Likewise, projects that were granted to communities to rebound and recover from devastating catastrophes (immediate relief and response funds and clean-up and wreckage removal projects) also have loss-reducing effects. However, most expensive protective/defensive measures exhibit loss-inducing characteristics, and to some extent almost outweighs loss-reducing effects of building codes and design studies (marginal effects of Type II and Building Codes and Designs are of almost similar magnitude but of opposite signs). These findings urge policy makers to rethink traditional loss mitigation options, especially if changes in environment are unavoidable. As many occasions have proven (Katrina, 2005; Japanese Tsunami in 2010 and many others), there is no full protection from these adverse natural hazards and structural projects sometimes fail to protect if severity of hazard exceeds their designed capacity. Since we have to live with disasters and adapt to changing environments, maybe getting out of the way of disaster is a better solution than controlling raging nature. Alternatively, it might be recommended to restrict development in places protected by levees or dams to avoid potential catastrophes from structure failures. To summarize, we believe that public agencies should act with extreme caution and recognize that continuous provision of public protection could distort incentives of other actors exposed to risks to self-protect and may not always promote sustainable hazard mitigation direction.

[21] We have performed several robustness checks to validate the results including estimating the model by adding explanatory variables one by one. We find that both signs and significance of variables have remained consistence. Additionally, the results were found to be consistent when we estimate the model on a sub-sample of coastal counties. The coefficient for Type II adaptation measures were found insignificant, however positive, when the model was estimated using the Correlated Random Effects Tobit specification.

VI. Conclusions

In this paper we use panel data of the counties experiencing property losses from hurricanes of North-Atlantic basin in the period of 1989-2009 to identify the effects of various public protective measures and coping strategies on mitigating property losses. Controlling for physical and economic exposure, as well as socio-economic and infrastructure vulnerability of exposed regions, we are able to directly test the effectiveness of different public policy directions. This is provided by our ability to contrast different policy options both structural and non-structural based on project activities defined under FEMA Public Assistance and Hazard Mitigation Programs. Our empirical results show that the most effective mitigation policies are those that involve public investment in non-structural mitigation measures such as zoning and other standards regulations, hazard planning and identification strategies as well as effective enforcement of building codes.

We find some evidence that protective and defensive measures that are designed to mitigate direct disaster impacts actually amplify these shocks and fail to protect. This is likely to happen because of capacity limits, or because these measures could induce development and/or promote moral hazard. Often times, neglecting vulnerable and disaster prone communities is neither a politically nor a morally feasible option for policy makers. Nonetheless, when allocating disaster mitigation funds, they should be aware about perverse impacts of public protection on private behavior and be warrant that continuous protection could potentially alter risk perception. Further research is clearly recommended to identify potential evidence of moral hazard and in particular, explicit treatment is needed to establish relationship between these structural projects and private agents’ behavior. Promoting incentive based programs to encourage local level adaptation proved to be an effective loss mitigation strategy and could correct the distortions created by public involvement. Our sample analysis reveals that disaster preparedness, coping and recovery greatly depend on coordinated actions of federal and local authorities and private individuals exposed to risk. More stringent regulation of codes, hazard identification, planning, and enforcement of certain hazard mitigation policies, along with improved planning, awareness and warning systems provide cost-saving solutions for very costly environmental disasters.

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Figures

Figure 1. Decade-by-decade trend of the cost of hurricanes

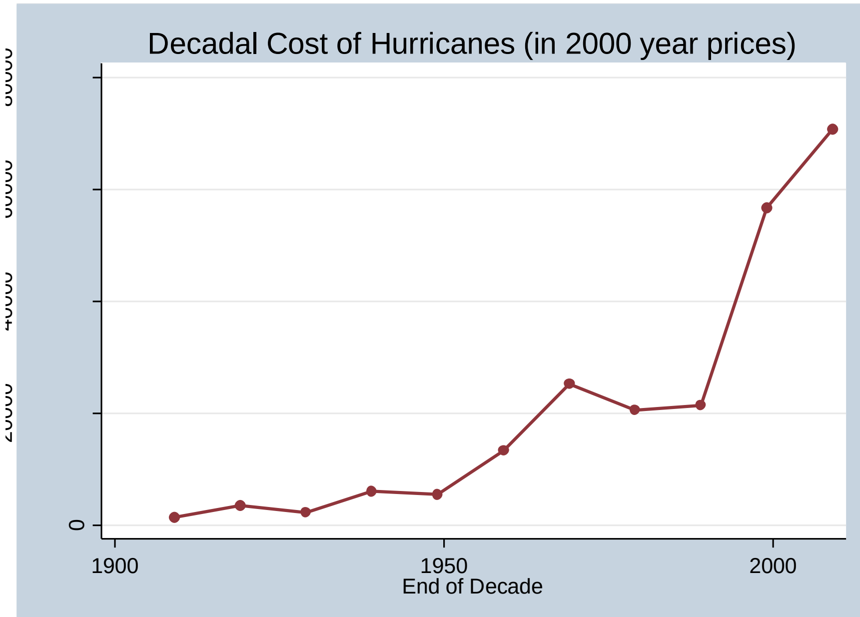
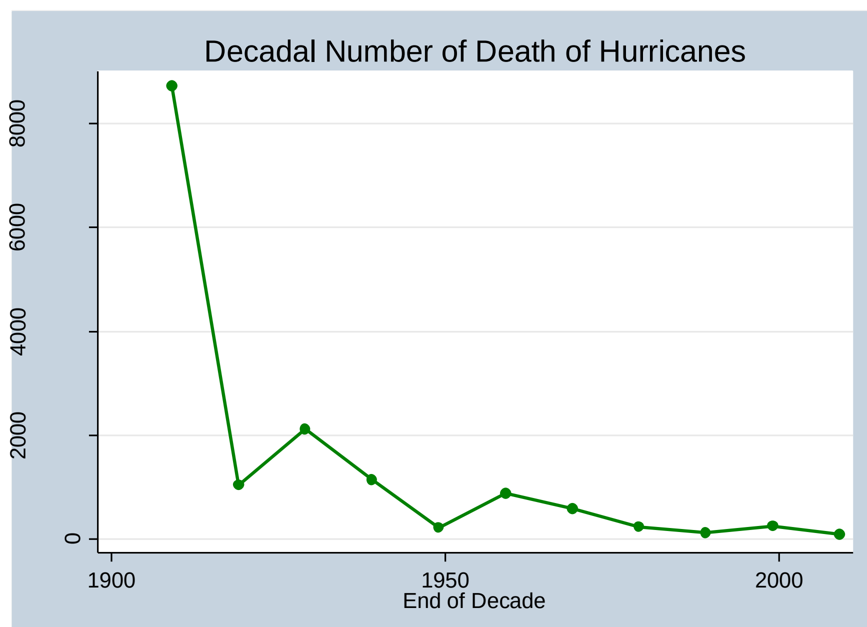


Figure 2. Decade-by-decade trend of the death of hurricanes



Source: Sheets B., and J. Williams, Hurricane Watch, 2001.

Figure 3. FEMA Hazard Mitigation Grant Projects

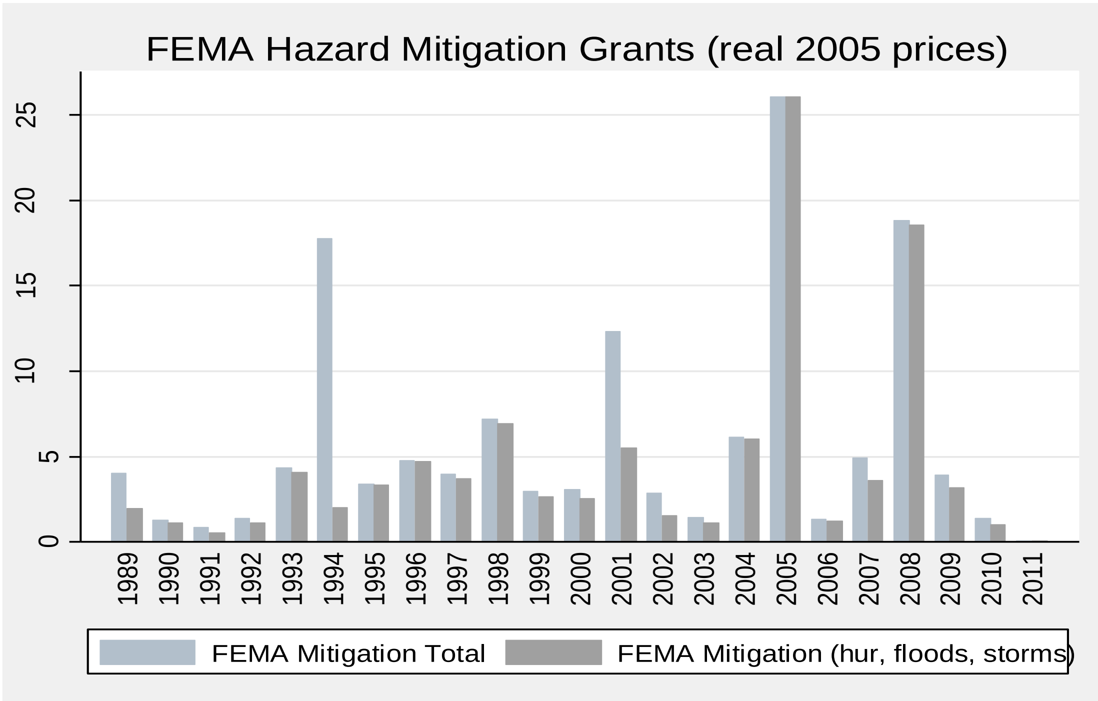
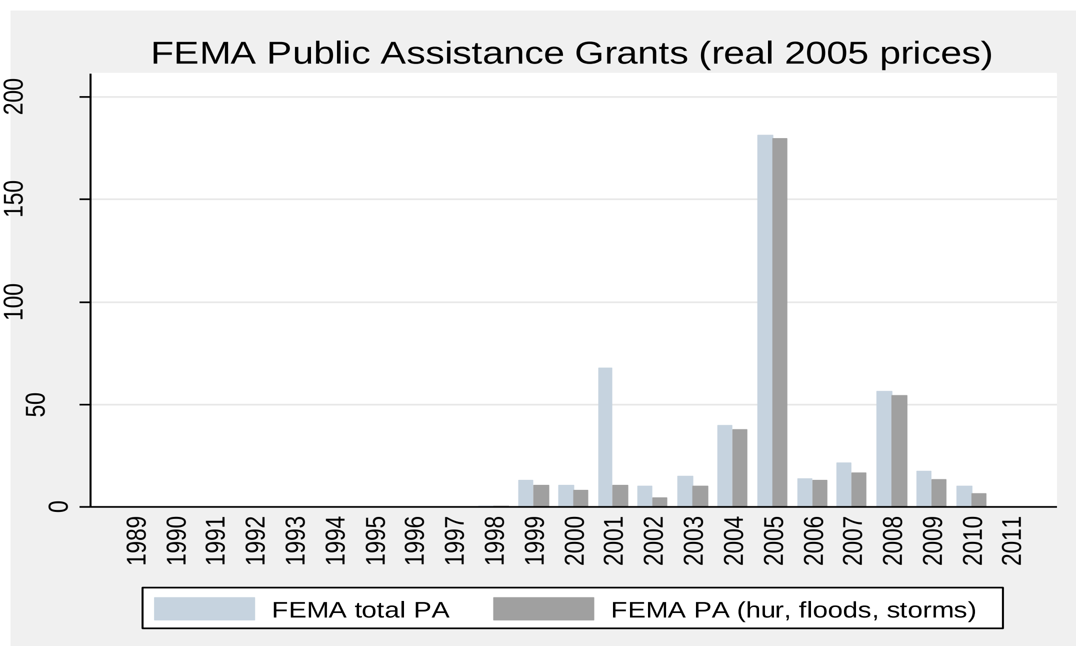


Figure 4. FEMA Public Assistance Grant Projects



Source: Federal Emergency Management Agency

Figure 5. Sample Counties

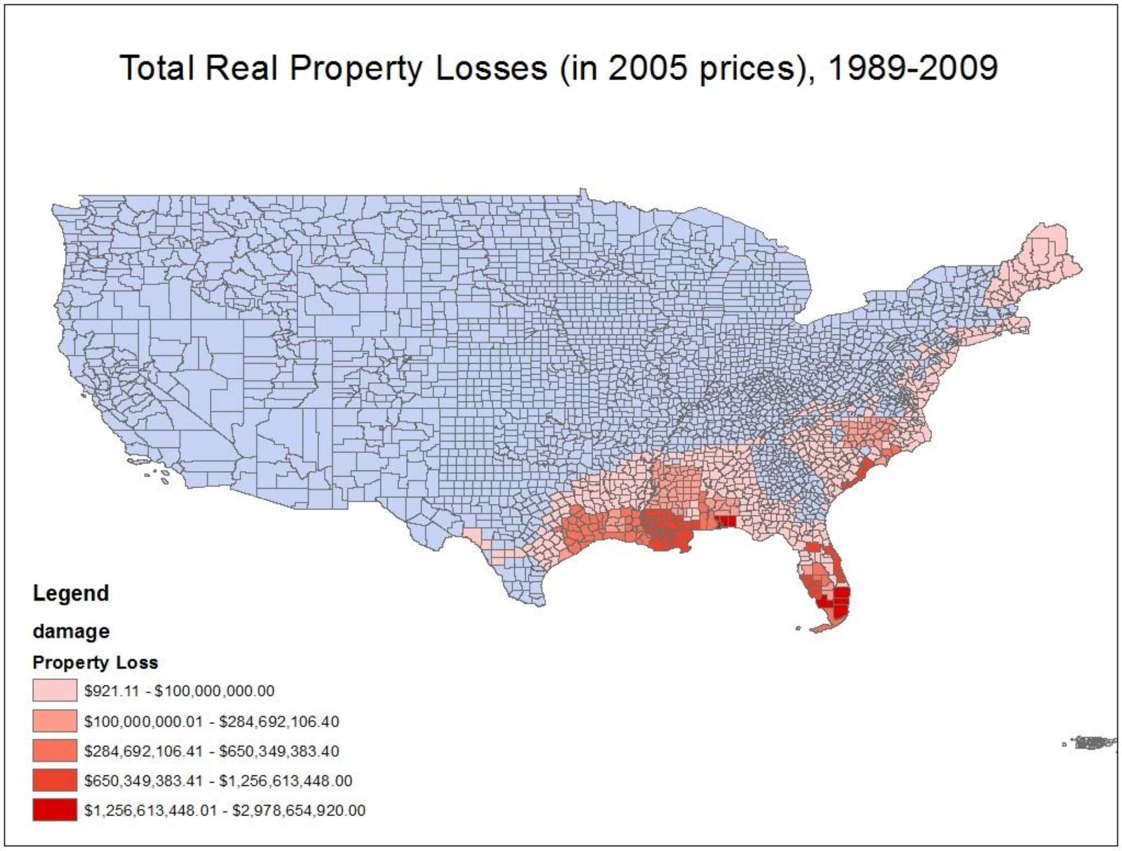
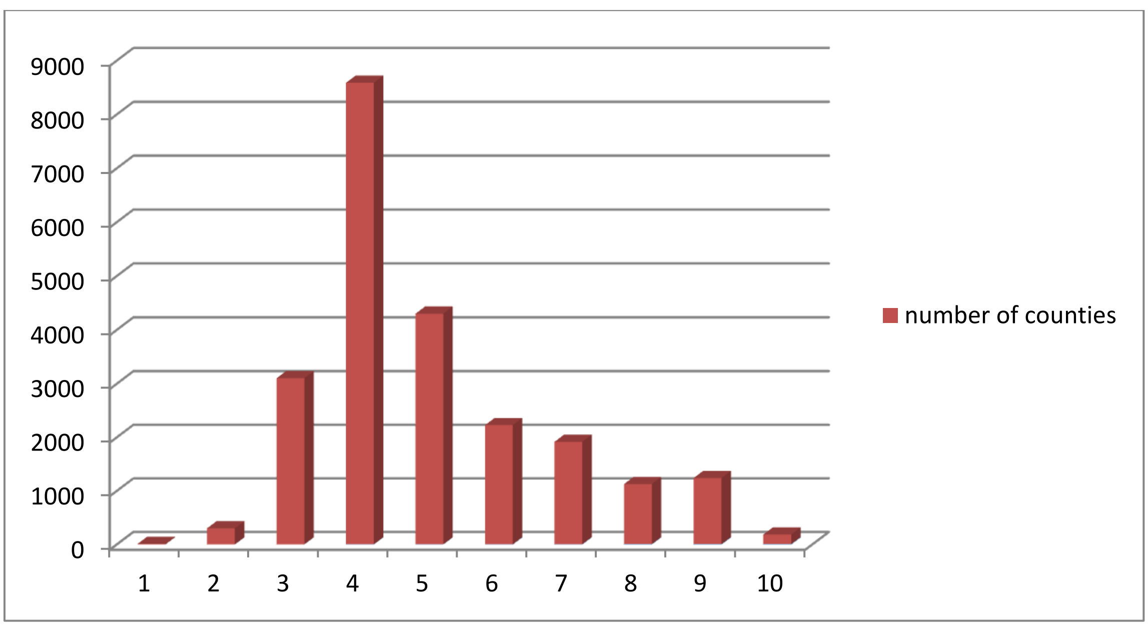


Figure 6. Distribution of counties by the BCEGS grading class (1-10)



Source: Insurance Services Office

Tables

Table 1: Summary Statistics

Variable Name	Mean	Std. Dev	Min	Max
Real Per capita property loss	99.28577	1351.083	0	101855.2
Log of real per capita income	10.13052	0.271773	8.967546	11.59713
Per capita vulnerable housing	0.134508	0.062948	0	0.797241
Unemployment rate	6.276892	2.859409	0.8	40.8
1-year lag of population change	13.89288	3592.539	-239913	326205
1-year lag of establishment change	-5.39138	140.9271	-3399	2410
Count of hurricane (cat.1-5) hits by a county in a given year	0.055961	0.240917	0	3
1-year lag of cumulative hits of hurricanes, (cat.1-5)	0.85897	3.174273	0	39
Major hurricane cat (3-5) (dummy = 1 if county hit by MH)	D=1 for 2.96%	D=0 for 97.04%	0	1
1-year lag of other disasters declared by the president	0.310069	0.569731	0	4
Dummy Coastal county * Tropical Cyclones	0.066667	0.283954	0	3
Building code & engineering designs studies (FEMA grants)	0.05368	0.362448	0	5.324665
BCEGS – dummy = 1 for counties with CRS class 7 or less	0.93125	0.253036	0	1
CRS total credit points	97.74844	351.1044	0	3001
Type I - general equilibrium adjustment (FEMA grants)	0.134488	0.4983	0	6.476165
Type II - Protective/defensive measures	0.205833	0.713653	0	8.429719
Type III - Adaptive/Coping measures	1.523146	3.745655	0	37.14602

Table 2: Pooled Tobit Regression Results

Dep. Variable: real per capita property loss	**Coefficients**		
Log of per capita income	149691.6***	146858.9***	150226.0***
	(2.23)	(2.29)	(2.26)
Log of per capita income squared	-7011.7***	-6884.4***	-6991.9***
	(0.22)	(0.23)	(0.22)
Per capita vulnerable housing	18976.8***	19541.2***	19270.7***
	(126.20)	(128.50)	(127.50)
Unemployment rate	155.8***	123.1***	101.2***
	(3.06)	(3.09)	(3.08)
Lag of population change	0.0137***	0.00766***	0.0102***
	(0.00)	(0.00)	(0.00)
Lag of establishment change	0.163***	0.226***	0.152***
	(0.03)	(0.03)	(0.03)
Lag of cumulative hurricane hits cat. 1-5	-31.66***	-19.63***	-15.35***
	(1.25)	(1.38)	(1.40)
Hurricane hits cat. 1-5	2113.5***	2235.6***	2110.6***
	(70.55)	(69.64)	(69.51)
Dummy for Major Hurricanes	1069.8***	1060.0***	1093.5***
	(100.60)	(99.69)	(100.40)
Lag of other types of disasters declared by a president	-257.3***	-263.8***	-278.4***
	(11.67)	(11.33)	(11.33)
Dummy for coastal county * tropical storms	424.6***	422.9***	486.5***
	(46.06)	(45.58)	(46.10)
CRS total credit points	-0.526***	-0.683***	-0.393***
	(0.02)	(0.02)	(0.02)
BCEGS (dummy = 1 if a county has CRS class category 7 and lower)	-300.1***	-392.8***	-278.9***
	(25.13)	(25.41)	(25.27)
2 year lag cumulative Type I (Warning and forecasting systems)	-415.6***		-468.0***
	(14.83)		(15.21)
2 year lag cumulative Type II (Structural & Infrastructural Projects)	228.5***		224.5***
	(7.90)		(8.24)
2 year lag cumulative Type III (adaptive/responsive measures)	-80.07***		-99.79***
	(2.33)		(2.40)
2 year lag cumulative Building Codes & design studies	-257.6***		-333.9***
	(13.88)		(14.74)
1 year lagged differences of Type I		-655.1***	-799.0***
		(52.16)	(53.50)
1 year lagged differences of Type II		-727.4***	-651.2***
		(25.57)	(26.15)
1 year lagged differences of Type III		-127.6***	-164.9***
		(7.22)	(7.23)
1 year lagged differences in Building Codes and design studies		-143.1***	-209.7***
		(32.39)	(32.27)
Constant	-829507.7***	-813758.2***	-836669.6***
	(22.62)	(23.20)	(22.89)
Sigma	3939.9***	3933.4***	3918.3***
	(7.19)	(7.16)	(7.17)
Number of observations	17280	17280	
Pseudo R-squared	0.1015	0.1017	
Log likelihood	-18761.373	-18756.163	

*p<0.05, **p<0.01, ***p<0.001; cluster standard errors in parenthesis; includes county and year fixed effects

Table 3: Average marginal effects (censored)

Dep. Variable: real per capita property loss	**Average ME for E(Y|X, Y>0)**		
Log of per capita income	7879.299***	7680.522***	7812.082***
	(149.30)	(149.88)	(152.25)
Log of per capita income squared	-369.0715***	-360.0463***	-363.592***
	(6.98)	(7.01)	(7.07)
Per capita vulnerable housing	998.8789***	1021.98***	1002.118***
	(25.54)	(26.64)	(26.13)
Unemployment rate	8.198969***	6.438758***	5.263709***
	(0.32)	(0.29)	(0.26)
Lag of population change	0.0007201***	0.0004004***	0.0005307***
	0.00	0.00	0.00
Lag of establishment change	0.008562***	0.0118015***	0.0079***
	(0.00)	(0.00)	(0.00)
Hurricane hits cat. 1-5	111.2485***	116.9171***	109.7576***
	(5.48)	(5.57)	(5.41)
Lag of cumulative hurricane hits cat. 1-5	-1.666263***	-1.026806***	-0.7980499***
	(0.05)	(0.06)	(0.06)
Dummy for Major Hurricanes	62.71808***	55.43653***	63.49664***
	(7.59)	(6.12)	(7.58)
Lag of other types of disasters declared by a president	-13.54604***	-13.7974***	-14.47689***
	(0.43)	(0.41)	(0.40)
Dummy for coastal county * tropical storms	22.35104***	22.11925***	25.30163***
	(2.76)	(2.73)	(2.79)
CRS total credit points	-0.0276939***	-0.0357285***	-0.0204294***
	(0.00)	(0.00)	(0.00)
BCEGS (dummy for a county with CRS class 7 or lower)	-15.79538***	-20.54468***	-14.50468***
	(1.03)	(0.93)	(1.03)
2 year lag cumulative Type I (Warning and forecasting systems)	-21.87539***		-24.3346***
	(0.85)		(0.86)
2 year lag cumulative Type II (Structural & Infrastructural Projects)	12.02885***		11.67301***
	(0.44)		(0.47)
2 year lag cumulative Type III (adaptive/responsive measures)	-4.214542***		-5.189262***
	(0.14)		(0.15)
2 year lag cumulative Building Codes & design studies	-13.55664***		-17.36131***
	(0.65)		(0.66)
1 year lagged differences of Type I		-34.26248***	-41.5491***
		(2.21)	(2.16)
1 year lagged differences of Type II		-38.04243***	-33.86135***
		(0.95)	(0.99)
1 year lagged differences of Type III		-6.675527***	-8.575314***
		(0.32)	(0.32)
1 year lagged differences in Building Codes and design studies		-7.486047***	-10.90232***
		(1.61)	(1.56)

Table 4: Average marginal effects (uncensored)

Dep. Variable: real per capita property loss	**Average ME for E(Y|X)**		
Log of per capita income	16.59429***	15.2789***	14.77354***
	(3.08)	(2.94)	(2.86)
Log of per capita income squared	-0.7772874***	-0.716242***	-0.6875941***
	(0.14)	(0.14)	(0.13)
Per capita vulnerable housing	2.103701***	2.03303***	1.895119***
	(0.40)	(0.40)	(0.38)
Unemployment rate	0.0172675***	0.0128087***	0.0099543***
	(0.00)	(0.00)	(0.00)
Lag of population change	0.00000152***	0.000000797***	0.000001***
	0.00	0.00	0.00
Lag of establishment change	0.000018***	0.0000235***	0.0000149***
	0.00	0.00	0.00
Hurricane hits cat. 1-5	0.2342961***	0.2325838***	0.2075642***
	(0.05)	(0.05)	(0.05)
Lag of cumulative hurricane hits cat. 1-5	-0.0035093***	-0.0020426***	-0.0015092***
	(0.00)	(0.00)	(0.00)
Dummy for Major Hurricanes	0.323561***	0.1102802***	0.1075392***
	(0.11)	(0.03)	(0.03)
Lag of other types of disasters declared by a president	-0.0285288***	-0.0274472***	-0.0273775***
	(0.00)	(0.00)	(0.00)
Dummy for coastal county * tropical storms	0.0470727***	0.0440019***	0.0478483***
	(0.01)	(0.01)	(0.01)
CRS total credit points	-0.0000583***	-0.0000711***	-0.0000386***
	0.00	0.00	0.00
BCEGS (dummy for a county with CRS class 7 or lower)	-0.033266***	-0.0408696***	-0.02743***
	(0.00)	(0.01)	(0.00)
2 year lag cumulative Type I (Warning and forecasting systems)	-0.0460709***		-0.0460195***
	(0.01)		(0.01)
2 year lag cumulative Type II (Structural & Infrastructural Projects)	0.0253335***		0.022075***
	(0.00)		(0.00)
2 year lag cumulative Type III (adaptive/responsive measures)	-0.0088761***		-0.0098135***
	(0.00)		(0.00)
2 year lag cumulative Building Codes & design studies	-0.0285511***		-0.0328322***
	(0.00)		(0.01)
1 year lagged differences of Type I		-0.0681585***	-0.0785741***
		(0.01)	(0.01)
1 year lagged differences of Type II		-0.075678***	-0.0640357***
		(0.01)	(0.01)
1 year lagged differences of Type III		-0.0132797***	-0.0162169***
		(0.00)	(0.00)
1 year lagged differences in Building Codes and design studies		-0.014892***	-0.0206175***
		(0.00)	(0.00)

Table 5: Pooled Tobit Regression Robustness Check

Dep. Variable: real per capita property loss	Coefficients						
Log of per capita income	86519.0*** (22265.10)	72437.6** (23146.80)	151837.3*** (2.27)	150969.1*** (2.27)	149864.4*** (2.28)	148265.1*** (2.21)	160141.9*** (2.39)
Income squared	-4107.3*** (1100.80)	-3433.9** (1143.70)	-7161.3*** (0.22)	-7118.2*** (0.22)	-7064.8*** (0.22)	-6976.6*** (0.22)	-7564.8*** (0.24)
Per capita vulnerable housing		11121.5* (4404.80)	19943.0*** (129.90)	20231.4*** (129.90)	20194.3*** (129.90)	19766.0*** (126.10)	20336.6*** (135.70)
Unemployment rate			131.4*** (3.31)	132.3*** (3.31)	132.6*** (3.31)	129.9*** (3.25)	159.5*** (3.32)
Lag of population change				0.0157*** (0.00)	0.0145*** (0.00)	0.0136*** (0.00)	0.0118*** (0.00)
Lag of establishment change					0.237*** (0.03)	0.275*** (0.03)	0.258*** (0.03)
Lag of cumulative hurricane hits (1-5_						-50.31*** (1.03)	-36.83*** (1.14)
Hurricane hits (cat. 1-5)							3089.0*** (25.93)

*p<0.05, **p<0.01, ***p<0.001; cluster standard errors in parenthesis; includes county and year fixed effects

Table 6: Pooled Tobit Regression Robustness Check (cont.)

Dep. Variable: real per capita property loss				**Coefficients**			
Log of per capita income	159805.3***	157855.8***	157735.4***	149077.4***	146175.4***	149734.0***	152453.6***
	(2.48)	(2.44)	(2.56)	(2.54)	(2.28)	(2.23)	(2.21)
Income squared	-7549.0***	-7454.7***	-7447.9***	-7021.1***	-6878.6***	-7029.5***	-7175.4***
	(0.24)	(0.24)	(0.25)	(0.25)	(0.23)	(0.22)	(0.22)
Per capita vulnerable housing	20474.3***	20416.2***	20489.8***	18929.0***	18979.9***	20489.8***	20494.6***
	(140.40)	(138.40)	(144.10)	(144.00)	(127.80)	(125.50)	(124.80)
Unemployment rate	159.0***	162.2***	161.9***	162.8***	163.5***	152.5***	156.4***
	(3.41)	(3.36)	(3.45)	(3.43)	(3.08)	(3.04)	(3.04)
Lag of population change	0.0116***	0.0108***	0.0109***	0.0116***	0.0113***	0.0123***	0.0118***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lag of establishment change	0.273***	0.289***	0.312***	0.222***	0.213***	0.303***	0.301***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Lag of cumulative hurricane hits (1-5_	-36.19***	-35.53***	-35.36***	-33.80***	-33.43***	-33.24***	-32.82***
	(1.14)	(1.13)	(1.33)	(1.32)	(1.27)	(1.23)	(1.20)
Hurricane hits (cat. 1-5)	2529.8***	2533.9***	2243.8***	2202.0***	2209.7***	2224.1***	2221.5***
	(40.46)	(40.53)	(71.58)	(71.34)	(70.58)	(70.57)	(70.49)
dummy for major hurricane hits	995.4***	985.8***	983.5***	1054.8***	1051.0***	1033.6***	1035.7***
	(79.46)	(79.51)	(101.30)	(100.90)	(100.10)	(100.20)	(100.10)
Lag of other types of disaster declaration		-233.5***	-231.6***	-255.6***	-253.5***	-269.8***	-267.4***
		(12.38)	(12.75)	(12.63)	(11.64)	(11.81)	(11.70)
Coastal dummy * tropical storms			384.9***	386.1***	381.1***	358.5***	364.9***
			(46.17)	(45.95)	(45.66)	(45.56)	(45.34)
CRS total credit points				-0.627***	-0.733***	-0.754***	-0.773***
				(0.01)	(0.01)	(0.01)	(0.01)
Building Codes enforcement effectiveness					-374.4***	-421.0***	-429.0***
					(25.38)	(25.04)	(24.93)
Type I (cumulative)						-504.8***	-555.8***
						(11.32)	(12.63)
Type II (cumulative)							121.1***
							(6.50)

*p<0.05, **p<0.01, ***p<0.001; cluster standard errors in parenthesis; includes county and year fixed effects

Table 7: Pooled Tobit Regression Robustness Check (cont.)

Dep. Variable: real per capita property loss	Coefficients						
Log of per capita income	149784.2*** (2.24)	149691.6*** (2.23)	150538.1*** (2.21)	150468.1*** (2.21)	150796.1*** (2.27)	150226.0*** (2.26)	146858.9*** (2.29)
Income squared	-7016.0*** (0.22)	-7011.7*** (0.22)	-7047.2*** (0.22)	-7026.8*** (0.22)	-7019.6*** (0.22)	-6991.9*** (0.22)	-6884.4*** (0.23)
Per capita vulnerable housing	19321.6*** (126.40)	18976.8*** (126.20)	20622.8*** (124.70)	21028.1*** (124.80)	19304.0*** (127.70)	19270.7*** (127.50)	19541.2*** (128.50)
Unemployment rate	154.6*** (3.07)	155.8*** (3.06)	139.2*** (3.05)	132.9*** (3.06)	102.1*** (3.08)	101.2*** (3.08)	123.1*** (3.09)
Lag of population change	0.0138*** (0.00)	0.0137*** (0.00)	0.0125*** (0.00)	0.0109*** (0.00)	0.0105*** (0.00)	0.0102*** (0.00)	0.00766*** (0.00)
Lag of establishment change	0.218*** (0.03)	0.163*** (0.03)	0.192*** (0.03)	0.203*** (0.03)	0.156*** (0.03)	0.152*** (0.03)	0.226*** (0.03)
Lag of cumulative hurricane hits (1-5_	-31.74*** (1.26)	-31.66*** (1.25)	-27.78*** (1.23)	-22.34*** (1.23)	-15.92*** (1.43)	-15.35*** (1.40)	-19.63*** (1.38)
Hurricane hits (cat. 1-5)	2131.1*** (70.60)	2113.5*** (70.55)	2153.4*** (69.78)	2176.8*** (69.48)	2119.9*** (69.51)	2110.6*** (69.51)	2235.6*** (69.64)
dummy for major hurricane hits	1051.9*** (100.80)	1069.8*** (100.60)	1029.4*** (100.00)	1026.4*** (99.54)	1080.7*** (100.70)	1093.5*** (100.40)	1060.0*** (99.69)
Lag of other types of disaster declaration	-257.8*** (11.71)	-257.3*** (11.67)	-262.2*** (11.86)	-247.1*** (11.53)	-275.2*** (11.29)	-278.4*** (11.33)	-263.8*** (11.33)
Coastal dummy * tropical storms	409.7*** (46.20)	424.6*** (46.06)	457.7*** (45.66)	448.9*** (45.46)	488.3*** (46.08)	486.5*** (46.10)	422.9*** (45.58)
CRS total credit points	-0.571*** (0.02)	-0.526*** (0.02)	-0.558*** (0.02)	-0.540*** (0.02)	-0.406*** (0.02)	-0.393*** (0.02)	-0.683*** (0.02)
Building Codes enforcement effectiveness	-341.5*** (25.16)	-300.1*** (25.13)	-334.3*** (24.89)	-346.5*** (24.91)	-301.7*** (25.35)	-278.9*** (25.27)	-392.8*** (25.41)
Type I (cumulative)	-395.2*** (14.85)	-415.6*** (14.83)	-502.3*** (15.08)	-498.8*** (15.25)	-464.0*** (15.26)	-468.0*** (15.21)	
Type II (cumulative)	222.8*** (7.54)	228.5*** (7.90)	237.9*** (7.99)	202.1*** (8.07)	221.4*** (8.09)	224.5*** (8.24)	
Type III (cumulative)	-89.11*** (2.21)	-80.07*** (2.33)	-84.80*** (2.36)	-80.36*** (2.39)	-100.9*** (2.40)	-99.79*** (2.40)	
Building code and design studies (cumulative)		-257.6*** (13.88)	-267.5*** (14.11)	-303.9*** (14.62)	-311.7*** (14.65)	-333.9*** (14.74)	
Type I (difference)			-1344.6*** (41.18)	-1144.3*** (39.87)	-764.9*** (52.81)	-799.0*** (53.50)	-655.1*** (52.16)
Type II (difference)				-872.6*** (20.29)	-652.6*** (26.83)	-651.2*** (26.15)	-727.4*** (25.57)
Type III (difference)					-179.2*** (6.94)	-164.9*** (7.23)	-127.6*** (7.22)
Building Code and Design Studies (difference)						-209.7*** (32.27)	-143.1*** (32.39)

*p<0.05, **p<0.01, ***p<0.001; cluster standard errors in parenthesis; includes county and year fixed effects

Table 8: Pooled Tobit vs. Correlated Random Effects Model, Robustness Check (cont.)

Dependent variable: real per capita property loss	Pooled Tobit, clustered standard errors; includes year and county dummies	CRE, bootstrapped standard errors (50 rep); no year dummies	CRE, bootstrapped standard errors (100 rep), includes year dummies; seed (123)
Log of per capita income	150226.0***	85670.9***	64539.5**
	(2.26)	(23077.10)	(20130.00)
Income squared	-6991.9***	-3775.3***	-2933.4**
	(0.22)	(1101.00)	(973.10)
Per capita vulnerable housing	19270.7***	29197.3***	34083.7***
	(127.50)	(5229.70)	(6476.40)
Unemployment rate	101.2***	32.15	103.4
	(3.08)	(41.50)	(57.62)
Lag of population change	0.0102***	0.0064	0.0126
	(0.00)	(0.02)	(0.02)
Lag of establishment change	0.152***	-1.153*	0.0548
	(0.03)	(0.56)	(0.39)
Lag of cumulative hurricane hits (1-5_	-15.35***	41.98**	-15.62
	(1.40)	(14.57)	(18.00)
Hurricane hits (cat. 1-5)	2110.6***	2391.7***	1635.2**
	(69.51)	(658.50)	(634.30)
dummy for major hurricane hits	1093.5***	1819.4***	1319.8***
	(100.40)	(467.00)	(380.40)
Lag of other types of disaster declaration	-278.4***	-493.9***	-280.9*
	(11.33)	(123.30)	(121.80)
Coastal dummy * tropical storms	486.5***	612.9**	653.2**
	(46.10)	(204.40)	(251.40)
CRS total credit points	-0.393***	-0.295	-0.373
	(0.02)	(0.25)	(0.25)
Building Codes enforcement effectiveness	-278.9***	-453.7*	-448.2
	(25.27)	(213.10)	(244.80)
Type I (cumulative)	-468.0***	-662.7***	-411.6**
	(15.21)	(144.60)	(140.80)
Type II (cumulative)	224.5***	108.6	163.7
	(8.24)	(107.10)	(122.10)
Type III (cumulative)	-99.79***	-85.93***	-89.35***
	(2.40)	(17.61)	(20.75)
Building code and design studies (cumulative)	-333.9***	-524.6***	-354.6*
	(14.74)	(148.20)	(156.10)
Type I (difference)	-799.0***	-1010.9**	-816.3*
	(53.50)	(363.40)	(398.60)
Type II (difference)	-651.2***	-1052.1***	-656.6**
	(26.15)	(266.40)	(244.10)
Type III (difference)	-164.9***	-23.92	-101.4*
	(7.23)	(41.46)	(41.82)
Building Code and Design Studies (difference)	-209.7***	207.9	-215.7
	(32.27)	(207.30)	(224.20)
Constant	-836669.6***	-389162.3***	-303579.1**
	(22.89)	(117984.40)	(104309.70)
Sigma u		1242.5***	1346.5***
		(222.00)	(213.60)
Sigma e		4358.0***	4100.1***
		(659.50)	(651.20)
Number of Observations	17280	17280	17280

*p<0.05, **p<0.01, ***p<0.001