

Examining the Impact on Mortality Arising from Climate Change: Important Findings for the Insurance Industry

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Abstract

In this paper, we analyze the impact on overall mortality rates for the general US population arising from climate change and the weather events resulting in property damages for the period 1968-2013. We develop a fixed effects panel data model for the impact of climate change on property damage, with precipitation having a more pronounced effect than extreme temperatures. Using the Dumitrescu-Hurlin panel data causality test, we found that property damages Granger cause an increase in mortality rates for the middle age and old age population. Therefore, property damage can further be used to improve the prediction of future mortality rates in the US. Our findings are important for the insurance industry, which is currently seeking ways to incorporate the impact of climate change. The industry is developing the Actuaries Climate Index and the Actuaries Climate Risk Index which have the objective of informing the insurance industry about the impact of extreme weather and its associated risks.

KEY WORDS: climate change, mortality, insurance, property damage, Dumitrescu-Hurlin causality test.

1 Introduction and Literature Review

The link between potential and actual increases in extreme weather events and climate change has long been established in the literature (Van Aalst, 2006; Schipper and Pelling, 2006; Hallegatte, 2014). The insurance industry has a strong interest in understanding the impact of climate change on insured exposures, for both people and property. For more than two decades, catastrophe modeling has been

extensively used by insurance and reinsurance companies to assess the impact of natural disasters and provide input in pricing, reserving, underwriting, risk management, reinsurance decision-making, portfolio optimization, and capital setting. Thus the mechanisms between climate change reflected through an increase in frequency and likelihood of extreme events and property losses are already modeled, and insurance policies account for the additional cost of natural disasters associated with climate change. A related body of literature addresses the impacts of climate change that induced catastrophic events on income levels and income distribution in affected areas (Masozera and Kerchner, 2007; Miljkovic and Miljkovic, 2014; Fang et al., 2017).

In addition to property losses caused by natural catastrophes, the insurance industry has recognized that human health, mortality, and morbidity are also linked to climate change. While direct human losses related to natural disasters are measurable, indirect losses such as decline in health or increase in morbidity are difficult to measure, thus leading most studies to focus on direct losses. The idea behind this approach is based on the premise that good macroeconomic data would account for both indirect and direct losses from significant disasters, so most of the studies focus on the impact of disasters on macroeconomic variables.

Deschenes and Greenstone (2011) used a state-by-year fixed effects model to quantify the relationship between mortality and daily temperatures in the U.S. for the period from 1968-2002. Their findings show that an additional day with a mean temperature exceeding 90°F leads to an increase in the annual age-adjusted mortality rate of about 0.11 percent while an additional day with a mean temperature below 20°F is associated with an increase in mortality of roughly 0.07-0.08 percent. Barreca (2012) found that humidity and temperature are important determinants of mortality for the period 1973-2002. He projected that the distributional impact of mortality rates is likely to change in the future, such as an increase in mortality for the hot areas and a decline in mortality in the cold areas of the US.

Patz et al. (2005) recognized two main impacts on health due to climate change, such as direct heat-related mortality and morbidity and an indirect climate-related risk of infectious diseases. Direct heat-related mortality is caused by the differences in extreme temperatures at the time of the year (e.g. early summer) when people have not yet become accustomed to these temperature swings.

However, climate projections indicate that these extremes may become more prevalent especially in mid-latitudes. The same authors indicated that heat-related mortality may increase in large cities and urban areas with population growth creating an “urban heat island effect”.

Several studies focused on developing index insurance linked to climate change forecasts. Kovacevic and Pflug (2011) analyzed the potential of insurance to escape a poverty trap. The relationship between insurance and inputs used in production, such as fertilizer and pesticide application rates, for both farm level insurance and index insurance was studied by Ramaswami (1993), Babcock and Hennessy (1996), Chambers and Quiggin (2002), and Mahul (2001). These studies do not address interactions between insurance, climate forecast and input decisions. Carriquiry and Osgood (2012) closed this gap in their study of Index Insurance, Probabilistic Climate Forecasts, and Production. The reinsurance industry has adopted a probabilistic seasonal climate forecast in pricing (Hellmuth et al., 2006). Chang et al. (2011) discussed evaluation of catastrophe equity puts.

Recent efforts by North American actuarial organizations, including the Society of Actuaries, the Casualty Actuarial Society, the American Academy of Actuaries, and Canadian Institute of Actuaries, was raised to develop an Actuaries Climate Index (ACI) and an Actuaries Climate Risk Index (ACRI) with the purpose to assist the insurance industry to quantify the effect of extreme weather and its associated risks. The report by Curry et al. (2012) lay the foundation for the development of the ACI and ACRI indexes as means of quantifying risk through the occurrence and frequency of climate extremes over time. The ACI is calculated as an unweighted average of standardized weather-related anomalies: temperature, precipitation, drought, wind, sea level, and soil moisture. The ACRI is based on the historical correlations of economic losses, mortality, and injuries arising from weather-related events.

The objective of this current paper is twofold. First, we test econometrically the direct impact of climate variables on property damages using a very detailed and large data set. This part of the paper not only adds to the existing body of literature already discussed, but provides more robustness due to a very large cross-section, time-series data set. The second objective is derived from the first one. Once the link between property damages and climate variables is confirmed, we econometrically establish the causality between property damages and mortality rates, hence adding yet a different

dimension to the studies on the impact of climate change on mortality.

There is no research to date, to the best of our knowledge, that addresses the link between the property damage due to catastrophic events caused by climate change and mortality rates. Anecdotal stories about catastrophic weather events causing health stresses abound, but there is no published research to that effect. Hence the question of interest in this article is: Is there a causal linkage between property damage due to catastrophes caused by climate change and mortality rates? The importance for the insurance industry of being able to establish such a link is obvious as such information could be used to predict mortality rates more accurately. If one is aware of the age-old issue of the relationship between the concepts of correlation and causality, it is clear that establishing causality is a necessary condition for credible prediction. This reasoning in economics goes back all the way to Stigler (1952) influential textbook on price theory, where he writes: “The important purpose of a scientific law is to permit prediction, and prediction is in turn sought because it permits control over phenomena. That control requires prediction is self-evident, for unless one knows what ‘causes’ a particular phenomenon, one cannot effect or prevent its occurrence.” Indeed, before more complex mortality models and indices are developed with a multitude of interactions in multivariate settings, establishing a causal relationship between climate-induced weather catastrophes and their resulting property damages and mortality rates is ultimately critical for predicting mortality rates more accurately.

This paper is organized as follows. In Section 2, we describe three big data sets used in this project. In Section 3 we discuss the panel data fixed effects, unit root tests, and panel data causality tests. The results are summarized in Section 4. Section 5 provides discussion of the findings and implications to the insurance industry.

2 Data Sources

The Mortality Data files include 35.7 million records reflecting 79.7 million deaths in the United States for period 1968-2013. The data for the period from 1999-2013 were provided by the National Center for Health Statistics (National Center for Health Statistics, 1999-2013) with a signed Data Use Agreement. The data for the period from 1989-1998 were provided by National Center for Health Statistics (National Center for Health Statistics, 1989-1998) with a signed Data Use Agree-

ment. These two signed Data Use Agreements have been obtained separately. While the data for the period 1989-2013 require a signed Data Use Agreement, the previous years data on death and population records are publicly available at the USA National Center for Health Statistics web site.

Based on information available in the Compressed Mortality Files (CMF), mortality rates were calculated, due to all-causes of deaths, for the time period 1968-2013, by county, state, and age groups 0-1, 1-44, 44-65, 65+. The aggregation of the mortality data by age group is consistent with the previous research done by Deschenes and Greenstone (2011) who used the mortality data for the period 1968-2002. The CMF reports death counts by race (White, Black, and other races), sex, age group, county of residence, cause of death (4-digit International Classification of Diseases code), and year of death. Additionally, the CMF files include population totals for four age groups, which we used to calculate all-cause mortality rates. Figure 1 displays the time series of mortality rates for adults 65+ for each US state from 1968-2013. The series from the states are grouped regionally and overlaid with a locally weighted scatterplot smoother (LOWESS), often referred to as a locally weighted smoother (LOESS) to emphasize regional trends (Cleveland, 1979). The downward trend is a reflection of an increase in longevity in the US population aged 65+ during this period, with a larger number of people constantly entering this group relative to those leaving it due to death. The previous research established that this age group is the most vulnerable when it comes to climate change impacts (Conti et al., 2007, 2005; Worfolk, 2000). Figure 2 represents the change in mortality rate in the US over time for the same age group. Property Losses Data has been provided by the Hazard & Vulnerability and Research Institute at the University of South Carolina. The Special Hazard Events and Losses Database for the United States (Hazards & Vulnerability Research Institute, 2015) provides county-level hazard loss data for the period 1960-2014 related to 18 different natural hazard events such as: thunderstorm, hurricanes, floods, wildfires, tornadoes, etc. Property losses are presented in constant 2014 US dollars. For an exact event, the database includes the event date, location (county and state), property losses, crop losses, count of injuries, and fatalities that affected each county. The total number of records included in (Hazards & Vulnerability Research Institute, 2015) is 857,318. Property losses include property damage to buildings of any type, i.e., residential, commercial, and public. These losses are all direct losses and do not include losses due to, for

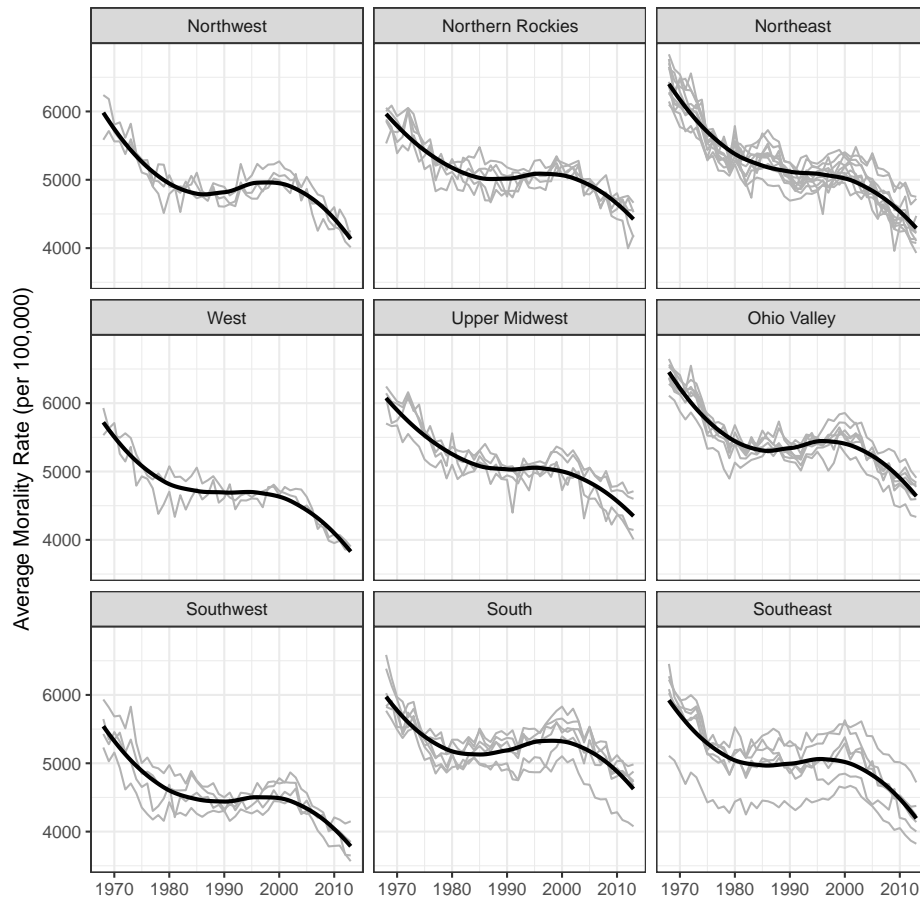


Figure 1: Time series of state mortality rates for adults 65+ from 1968-2013, grouped by region with LOESS smoothers overlaid to emphasize trend.

example, business interruption. Figure 5 shows the time series of the log of average property damage per capita by state overlaid by a bold smoother to highlight the general trend.

The climate data was taken from the Global Historical Climatology Network (GHCN)-daily weather database provided by the National Oceanic and Atmospheric Association (National Centers for Environmental Information, 2015). This data provides daily summary statistics on weather events from weather stations around the world. With our goal to analyze the relationship between mortality, losses, and climate on the annual county-level within the United State, it was necessary to restructure and augment the daily weather data to serve this purpose. On a high level, this involved two main stages (1) gathering, cleaning and combining the necessary information on all US counties and US-based weather stations, then (2) aggregating daily measurements from multiple stations into

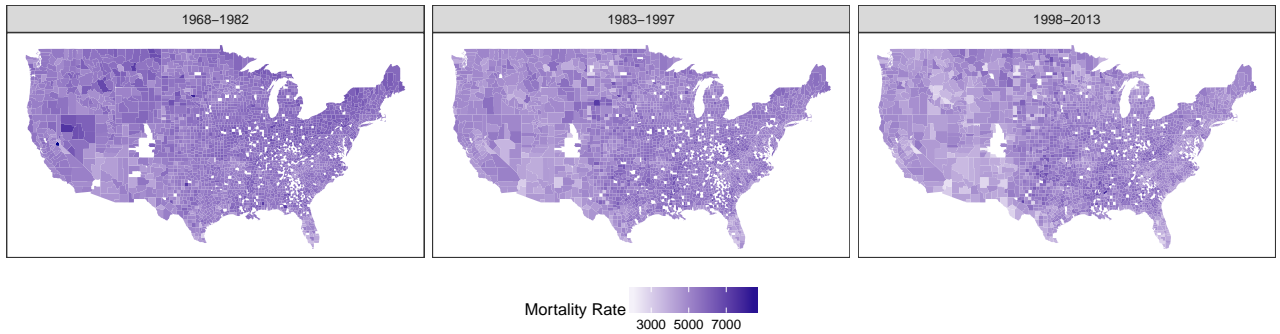


Figure 2: Mortality map for ages 65+. Average mortality rates (in 100,000) are computed for the periods: 1968-1982 (left), 1983-1997 (middle), 1998-2013 (right).

annual county-level metrics of climate that can be used in primary analysis. Two primary sources for information on member stations contribute to the GHCN: the Enhanced Member Station History Report (EMSHR) published by the National Centers for Environmental Information, and the GHCN station data. By combining the station information using unique identification numbers assigned by the GHCN we had access to the county where each station resides, the elevation and the longitude and latitude location of operation. The county's geographic centroid, obtained from the Gazetteer data from the US Census Bureau, were also merged into the station data for the purpose of subsequent aggregations. With the characteristics of the weather stations prepared, we were then ready to aggregate daily weather measurements into annual county-level climate metrics. In aggregating weather values into annual county-level summary statistics, we first impose a filter to remove observations from any weather station that is outside the continental US or above 7000ft elevation as they are considered to be outside the scope of the analysis. Next, daily county-level weighted averages for high temperature, low temperature, and precipitation are calculated using weights inversely proportional to the distance of weather stations from county centroids. While daily weather patterns are not likely to differ strongly in different areas in each county, the weighted averaging allows for the aggregates to be more representative the weather experienced by the residents across the entire county. It would be ideal to base the weights on the population density centroid of each county, but human populations have dynamic inter and intra-county movement over time that changes faster than our weather measurements are recorded. The geographic centroid provides a reasonable proxy for a

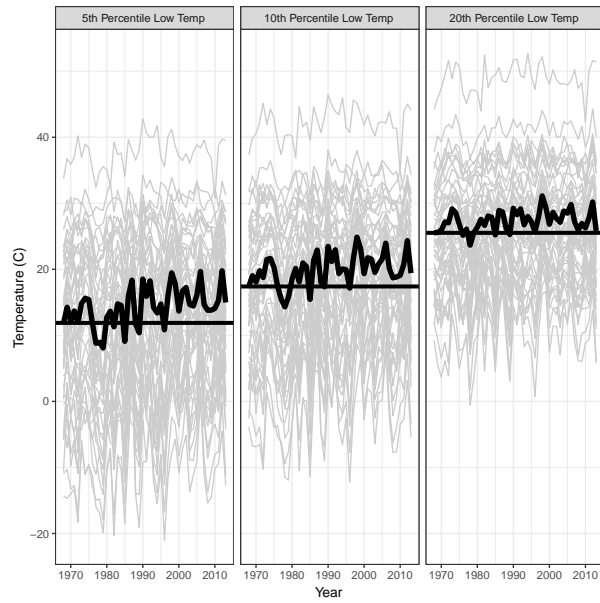


Figure 3: Time series of state low temperatures by state from 1968-2013, with LOESS smoother overlaid.

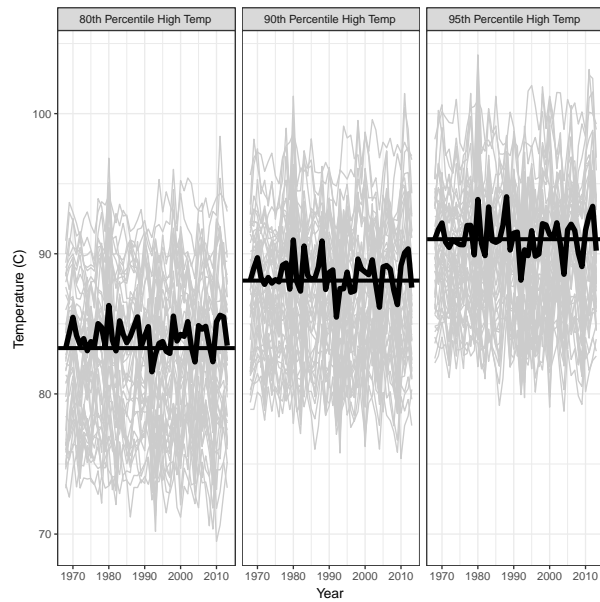


Figure 4: Time series of state high temperatures by state from 1968-2013, with LOESS smoother overlaid.

representative location where the county population will experience the daily weather.

Lastly, a number of annual county-level aggregations are constructed using these daily county-level weather averages with a focus to create weather metrics that reflect extreme behaviors that may impact mortality. For temperature, the extremes are captured using the 5th, 10th and 20th percentiles of low temperature, and the 80th, 90th and 95th percentiles for high temperature. In addition, ten temperature bins are created to allocate the number of days per year according to the temperature bins. These bins include: 0 – 10°F, 10 – 20°F, 20 – 30°F, 30 – 40°F, 40 – 50°F, 50 – 60°F, 60 – 70°F, 70 – 80°F, 80 – 90°F, 90+°F. Figure 3 shows the time series of low temperatures such as the 5th, 10th, and 20th percentiles by state, overlaid by a bold smoother to highlight the general trend. Figure 4 shows the time series of the 95th, 90th, and 80th percentiles of high temperatures by state. The plot is overlaid with the yearly average for these statistics by state.

Similarly, precipitation data were aggregated into same range of quantiles as temperature data. Ten bins are developed to allocate the precipitation data into different ranges. Additionally, standard deviation and average precipitation by state, county, and year are calculated.

3 Methodology

3.1 Panel Data Fixed Effects Model

We develop the region-specific fixed effects model based on county data. As both mortality and climate change phenomena evolve over time rather than have discrete changes in a particular year, then the use of time trend in lieu of the time fixed affects is considered more appropriate. The general form of this fixed effects model is presented below:

$$\ln(PD_{rct}) = \sum_i \alpha_i T_{rcti} + \sum_j \beta_j P_{rctj} + t + \gamma_r + \epsilon_{rct}$$

where PD_{rct} is the property damage per capita in a specific region r , county c , in year t . Here, T_{rcti} denotes number of days in temperature bin i , year t , county c , and region r . Similarly, the precipitation variable is denoted as P_{rctj} and it represents number of days in j^{th} precipitation bin or average precipitation variable as described in Section 2. Additionally, γ_r and t are cross-sectional

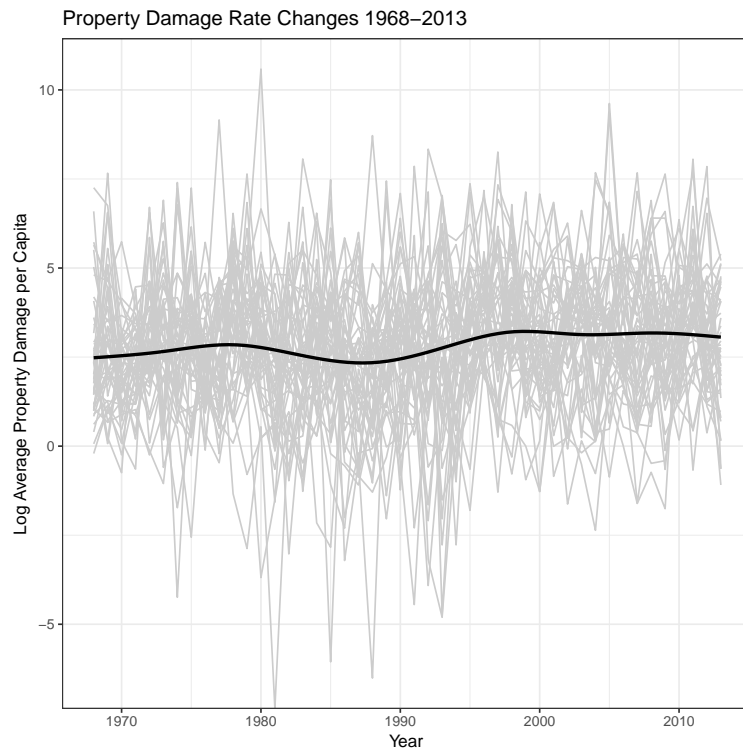


Figure 5: Time series of state property damage per capita from 1968-2013, with LOESS smoother overlaid.

regional dummy variables and time trend respectively. Finally, the last term in the equation ϵ_{rct} represents the stochastic error term. In this model, a small number of counties that have not reported any property damage are omitted from the analysis.

In order to compare models and check for the goodness of fit, the Akaike Information Criterion by Akaike (1974), is used to select the best model. The results of the final selected models are presented in Section 4.

3.2 Panel Data Unit Root Tests

The panel data cross-sectional time series analysis is a standard procedure to check for existence of unit roots. This panel unit root testing emerged from the time series unit root testing. However, contrary to time series testing of unit roots, in the panel data these unit root tests should consider asymptotic behavior of the time series and cross-sectional dimensions. In general, for panel unit root testing the following procedure is used:

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{l=1}^{p_i} \varphi_{i,l} \Delta y_{i,t-l} + \alpha_i d_{i,t} + \epsilon_{i,t}$$

where $d_{i,t}$ represents the deterministic (exogenous) component in the model, autoregressive coefficient $\rho = 0$ indicates that y process has a unit root for individual i , Δ denotes first difference operator, while $\rho < 0$ process is stationary around the deterministic part. Furthermore, p_i is the lag order for the difference terms, α_i is parameter associated with the exogenous component in the model that is to be estimated, and $\varphi_{i,l}$ is parameter associated with differenced y -series that is to be estimated. Levin et al. (2002) proposed a panel unit root test known as Levin-Lin-Chu Test (LLC) that considers the following hypotheses:

H0: each time series contains a unit root

H1: each time series is stationary

The null hypothesis is that time series for all cross-sectional units are non-stationary, while the alternative that all time series are stationary. The alternative hypothesis in this test suggests that ρ_i are

identical and negative.

Im et al. (2003) proposed another panel unit root test, known as IPS test, with a more general and less restrictive alternative to allow to vary so that some individual unit root process is possible. For this hypothesis test, it is suggested that:

H0: assumes all y_i follows unit root process

H1: not all follows y_i unit root process

The null hypothesis is that the time series for all cross-sectional units follow a unit root process, i.e., are not stationary, while the alternative hypothesis allows at least one time series to be stationary.

We apply these two unit root tests separately to property damage and mortality rate panel data.

3.3 Panel Data Granger Causality Tests

In panel data settings, least squares regressions can take a number of different forms, depending upon assumptions made about the structure of the panel data. Since Granger (1969) Causality is computed by running bivariate regressions, there are a number of different approaches to testing for Granger (1969) Causality in a panel context. In general, the bivariate regressions in a panel data context take the form:

$$y_{i,t} = \alpha_{0,i} + \alpha_{1,i}y_{i,t-1} + \dots + \alpha_{l,i}y_{i,t-l} + \beta_{1,i}x_{i,t-1} + \dots + \beta_{l,i}x_{i,t-l} + \epsilon_{i,t}$$

$$x_{i,t} = \gamma_{0,i} + \gamma_{1,i}x_{i,t-1} + \dots + \gamma_{l,i}x_{i,t-l} + \delta_{1,i}y_{i,t-1} + \dots + \delta_{l,i}y_{i,t-l} + \epsilon_{i,t}$$

where y and x denote two stationary variables, i.e., mortality rates and property damages in our study, observed for i cross-sectional dimensions (e.g., the county and state of residence) on t periods.

The different forms of panel causality tests differ regarding the assumptions made about the homogeneity of the coefficients across cross-sections. There are two approaches to causality testing in panels. The first is to treat the panel data as one large stacked set of data, and then perform the

Granger (1969) Causality test in the standard way, with the exception of not letting data from one cross-section enter the lagged values of data from the next cross-section. This method assumes that all coefficients are the same across all cross-sections, i.e.:

$$\alpha_{0,i} = \alpha_{0,j}, \alpha_{1,i} = \alpha_{1,j}, \dots, \alpha_{l,i} = \alpha_{l,j}, \forall i, j$$

$$\beta_{1,i} = \beta_{1,j}, \dots, \beta_{l,i} = \beta_{l,j}, \forall i, j$$

$$\gamma_{0,i} = \gamma_{0,j}, \gamma_{1,i} = \gamma_{1,j}, \dots, \gamma_{l,i} = \gamma_{l,j}, \forall i, j$$

$$\delta_{1,i} = \delta_{1,j}, \dots, \delta_{l,i} = \delta_{l,j}, \forall i, j$$

A second approach adopted by Dumitrescu and Hurlin (2012) uses more generalized assumptions, allowing all coefficients to be different across cross-sections:

$$\alpha_{0,i} \neq \alpha_{0,j}, \alpha_{1,i} \neq \alpha_{1,j}, \dots, \alpha_{l,i} \neq \alpha_{l,j}, \forall i, j$$

$$\beta_{1,i} \neq \beta_{1,j}, \dots, \beta_{l,i} \neq \beta_{l,j}, \forall i, j$$

$$\gamma_{0,i} \neq \gamma_{0,j}, \gamma_{1,i} \neq \gamma_{1,j}, \dots, \gamma_{l,i} \neq \gamma_{l,j}, \forall i, j$$

$$\delta_{1,i} \neq \delta_{1,j}, \dots, \delta_{l,i} \neq \delta_{l,j}, \forall i, j$$

This test is calculated by running standard Granger Causality regressions for each cross-section individually. The next step is to take the average of the test statistics, which is termed the W-bar

statistic. They show that the standardized version of this statistic, appropriately weighted in unbalanced panels, follows a standard normal distribution. This is termed the Z-bar statistic. Dumitrescu and Hurlin (2012) is the method/test used in this paper.

Just as in Granger (1969), the procedure to determine the existence of causality is to test for significant effects of past values of x on the present value of y . The null hypothesis is therefore defined as: $H_0 : \beta_{1i} = \dots = \beta_{li} = 0, \delta_{1i} = \dots = \delta_{li} = 0, \forall i$ which corresponds to the absence of causality for all cross-sections in the panel. The test assumes there can be causality for some cross-sections, but not necessarily for all. In other words, if the null hypothesis is rejected, there can be causality for some cross-sections but not necessarily for all, while the null hypothesis is not rejected, there is no causality in any cross-sections.

4 Results

4.1 Fixed Effects Model Results

Table 1 summarizes the results from the fixed-effects regression model between property damage and climate variables to account for regional variations and time trend. Nine climate regions within the contiguous United States are defined by the National Centers for Environmental Information and are useful for putting current climate anomalies into a historical perspective (Karl and Koss, 1984). These regions defined by state are as follows: Northwest (ID, OR, WA), Norther Rockies (MT, NE, ND, SD, WY), West (CA, NV), Southwest (AZ, CO, NM, UT), South (AR, KS, LA, MS, OK, TX), Southeast (AL, FL, GA, NC, SC, VA), Upper Midwest (IA, MI, MN, WI), Ohio Valley (IL, IN, KY, MO, OH, TE, WV), and Northeast (CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT). Based on Akaike (1974) criteria, the best model contains only extremely high and low temperature variables and average precipitation as measures of climate change. The overall R^2 reported for this model is 91% indicating that the model fits very well.

The results in Table 1 show that climate variables have a significant impact on property damages. The impact of precipitation is much higher than the impact of both high and low temperatures, given the size of the coefficient estimate for the Average Precipitation variable. An increase of precipitation

Table 1: Fixed-effects regression results between log of property damages per capita and climate variables for period 1968-2013 and the age group 65+.

Variable	Coefficient	SE	p-value
Intercept	-10.67000	1.21100	< 2e-16***
Northern Rockies	1.35800	0.04970	< 2e-16***
West	0.03007	0.06829	0.65965
Southwest	0.36610	0.05759	2.06e-10 ***
South	1.16300	0.04425	< 2e-16***
Southeast	-0.03652	0.04616	0.42891
Upper Midwest	0.42500	0.04917	< 2e-16***
Ohio Valley	0.02165	0.04469	0.62799
Northeast	-0.15130	0.04937	0.00218 **
year	0.00543	0.00061	< 2e-16***
TMEAN9	0.00804	0.00252	0.00143 **
TMEAN1	0.02255	0.00106	< 2e-16***
avgPrcp	6.27800	0.19870	< 2e-16***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Multiple R-squared: 0.91234, Adjusted R-squared: 0.90522 F-statistic: 461.1 on 12 and 100171 DF, p-value: < 2.2e-16***
AIC: 187079.2

Note: TMEAN1 and TMEAN9 variables represent the yearly counts of days with average temperatures in Fahrenheit falling into the bins 10 – 20°F, 90+°F respectively. The avgPrcp variable represents the average daily precipitation as measured in inches.

of an inch per sq. foot leads to an increase in average property damage by \$528. That result is expected given the multiple ways in which precipitation can damage various structures, unlike extreme temperature that takes a longer time to have a measurable effect.

The coefficients of regional dummies, relative to the Northwest are all positive, except for the South East and Northeast where the coefficients are negative, but only the North East coefficient is statistically significant. This can be explained by the fact that the Northwest region that serves as the base region is known to have large annual precipitations and as well as extremely low temperatures relative to the Northeast region. We also observed positive and statistically significant coefficients associated with climate variables indicating low temperature in bin 10 – 20°F and high temperature in bin 90 – 100°F. The variables corresponding to these low and high temperatures bins are denoted as “TMEAN1” and “TMEAN9”. Time trend (“year” variable) is positive, meaning that there is an increase in property damage over time reflecting an increase in property values and the number of

Table 2: Summary of panel unit root test: property damage by state, 1968-2013.

Levin, Lin & Chu Test			
Null Hypothesis: assumes common unit root process			
Stat	p-value	cross-section	observations
-23.0517	0.0000	48	2112
Im, Pesaran and Shin Test			
Null Hypothesis: assumes individual unit root process			
Stat	p-value	cross-section	observations
-21.9882	0.0000	48	2112

properties. An additional day of extreme temperatures in bin 90 – 100°F increases, on average, property damage per capita by 0.8%, while an additional day of extremely low deprecates in bin 10 – 20°F increases property damage per capita by 2.3% on average, holding all other variables constant. Based on Figure 3, however, we can see that global warming as a manifestation of climate change led to an increase in the trend of the quantiles of the lowest temperatures, thus, moderating an otherwise strong impact of extremely low temperatures on property damages. These results are produced using estimation tools available in the open-source environment for statistical computing and graphics R (R Core Team, 2016).

4.2 Unit Root and Granger Causality Tests Results for Old Age Population

Panel data-specific causality testing is conducted in EViews v.8. We apply both LLC and IPS unit root tests separately to property damage and mortality rate panel data. We reiterate here what we stated in the data section: we use mortality rate data for the segment of the population aged 65+ as it has already been conclusively determined in the literature that they are the most vulnerable population group to the impacts of climate change. Results of the panel unit root tests are presented for both series in Table 2 and Table 3, respectively. Both tests reject the null hypothesis of a unit root at least at 5% significance level; hence the series is stationary at levels. Results of the panel data Granger causality Dumitrescu-Hurlin pairwise tests are presented in Table 4. Again, the Dumitrescu and Hurlin (2012) test is a test of the Homogenous Non Causality (HNC) hypothesis. Under the null hypothesis, there is no causal relationship for any of the units of the panel. As the null hypothesis of non-causality is

Table 3: Summary of panel unit root test: mortality rates for the population aged 65+, by state, 1968-2013.

Levin, Lin & Chu Test			
Null Hypothesis: assumes common unit root process			
Stat	p-value	cross-section	observations
-5.09807	0.0000	48	2112
Im, Pesaran and Shin Test			
Null Hypothesis: assumes individual unit root process			
Stat	p-value	cross-section	observations
-2.23315	0.0128	48	2112

Table 4: Pairwise Dumitrescu-Hurlin panel causality tests for the population aged 65+.

Null Hypothesis: Average property damage does not homogeneously cause average mortality rates		
W-Stat	Zbar-Stat	p-value
1.67820	2.82174	0.0048
Null Hypothesis: Average mortality rates do not homogeneously cause average property damage		
W-Stat	Zbar-Stat	p-value
1.40816	1.60879	0.1077

rejected at a 1% significance level for the property damages not causing the mortality rates, we can conclude that property damages Granger cause the mortality rates. Notice that the Granger causality test is a statistical hypothesis test for determining whether the past values of one time series are useful in forecasting another time series current (future) values; it is not a “true causality” test.

4.3 Unit Root and Granger Causality Tests Results for Subgroups of Old Age Population

Mortality behaves considerably differently for the “young old” and for the “very old” (Waldron, 2007). In other words, mortality rates for different subgroups of the old age population, i.e., 65+, are potentially influenced by various, often differing factors. To that effect, and to test the robustness of our findings, we divided our 65+ age group into three subgroups: “young old” being in the interval 65-74, “intermediate old” being in the interval “75-84,” and “very old” being 85 and older.

First, panel unit-root tests are run for the average mortality rates for each of the subgroups. Results of the panel unit root tests are presented in Table 5. Both the LLC and the IPS tests indicate, at better than 1% significance level, that the series are stationary. Mortality rates across different age groups are likely to exhibit changing means and/or trends over time. Wider the age group range considered, more likely it will contain heterogeneous breaks in both the level and trend of the series. Hence, it comes as no surprise that, while both the overall old age group and individual subgroups unit root test results indicate stationarity at significance levels of 1%, the evidence of no unit root is even stronger for more homogeneous, narrower ranges of three old age population subgroups. Please note that the average property damages do not change, and the unit root test results reported previously still hold. Next, the panel data Granger causality Dumitrescu-Hurlin pairwise tests are run for each subgroup, and the results are provided in Table 6. Test results indicate (at 1% significance level) that average property damages Granger cause average mortality rates for both “young old” and “intermediate old” subgroups. Same does not hold true for the “very old subgroup.” These results not only reinforce the results for the entire old age population, reported in previous section of the paper, but are interesting in their own right. As mortality rates increase as we move from “young old” to “very old,” the causes that impact them change as well. Therefore, relatively largest mortality rates in the “very old”

Table 5: Summary of panel unit root test: mortality rates by state by old age subgroup, 1968-2013.

Levin, Lin & Chu Test				
Null Hypothesis: assumes common unit root process				
Subgroup	Stat	p-value	cross-section	observations
65-74	-23.7130	0.0000	48	2112
75-84	-23.4525	0.0000	48	2112
85+	-12.3621	0.0000	48	2112
Im, Pesaran and Shin Test				
Null Hypothesis: assumes individual unit root process				
Subgroup	Stat	p-value	cross-section	observations
65-74	-26.9026	0.0000	48	2112
75-84	-27.1905	0.0000	48	2112
85+	-17.7261	0.0000	48	2112

subgroup might be considered autonomous as the probability of dying for individuals in that subgroup approaches certainty. Hence any exogenous individual cause or impact on mortality rate of the “very old” population is likely to have relatively lesser impact than on other subgroups of the old age group. The strongest causal relationship, based on Dumitrescu-Hurlin pairwise test results, between average property damage and mortality rate of the “young old” subgroup serves as further confirmation of this line of reasoning.

4.4 Unit Root and Granger Causality Tests Results for Middle Age Population

We extend our analysis for the middle age population, i.e. group of 45-64 years of age. Middle age population is fairly uniform when it comes to the mortality rate as well as its socio-economic status. Hence, no further disaggregation of this data group is warranted. Panel unit root tests confirm, at 5% significance level, that series on mortality rate of middle age population is stationary (Table 7), while data on property damages remains as before; thus, the series is stationary at levels. Dumitrescu-Hurlin test indicates that property damages Granger cause and thus have an impact on mortality rates of this age group too (Table 8). Panel data Dumitrescu-Hurlin Granger causality test was run the age group 1-44, and could not be statistically confirmed for that age group 1-44. This result, however, should be taken with a cautionary note. We recognize that this age group is very diverse in terms of

Table 6: Pairwise Dumitrescu-Hurlin panel causality tests by old age subgroup.

Null Hypothesis: Average property damage does not homogeneously cause average mortality rates			
Subgroup	W-Stat	Zbar-Stat	p-value
65-74	2.16269	4.99792	0.0000
75-84	1.81460	3.43439	0.0006
85+	1.38747	1.51584	0.1296

Null Hypothesis: Average mortality rates do not homogeneously cause average property damage			
Subgroup	W-Stat	Zbar-Stat	p-value
65-74	1.10352	0.24041	0.8100
75-84	0.74653	-1.36313	0.1728
85+	1.28655	1.06253	0.2880

Table 7: Summary of panel unit root test: mortality rates by state for age 45-64, 1968-2013.

Levin, Lin & Chu Test			
Null Hypothesis: assumes common unit root process			
Stat	p-value	cross-section	observations
-2.09169	0.0370	48	2112

Im, Pesaran and Shin Test			
Null Hypothesis: assumes individual unit root process			
Stat	p-value	cross-section	observations
-2.05335	0.0200	48	2112

Table 8: Pairwise Dumitrescu-Hurlin panel causality tests for age 45-64.

Null Hypothesis: Average property damage does not homogeneously cause average mortality rates		
W-Stat	Zbar-Stat	p-value
1.81821	3.45063	0.0006

Null Hypothesis: Average mortality rates do not homogeneously cause average property damage		
W-Stat	Zbar-Stat	p-value
1.21459	0.73929	0.4597

biological and socio-economic attributes that might impact mortality rates, and statistical tests might be biased and thus misleading. Moreover, from life insurance standpoint, this age group is least likely to participate in that market, especially younger segment (children, teenagers, young adolescents) of that group. Thus, life insurance industry may not have same interest in these results given relatively small market share of this age group. For that reason, we do not present these results in the paper. However, these results are available, per readers' request, from the authors.

5 Discussion and Implications

The objectives of this paper are to confirm that climate change weather events significantly contribute to property damages, which in turn impact mortality rates. Weather events that proxy climate change are the extreme temperatures and average precipitation over time. The comprehensive climate variables data base is comprised of data collected from multiple weather stations in all U.S counties over the period 1968-2013. Results of the fixed-effects panel data model reaffirm our knowledge about the impact of climate change on property damages, with precipitations having a more pronounced effect than the extreme temperatures. Property damages are found, in turn, to Granger cause mortality rates in the U.S. during this same period.

The use of Granger causality test results should be applied with caution when considering more complex multivariate models in trying to explain current and past behavior of the variable of interest, as well as to predict the impact of various regressors on its future values. It is suggested that a Bayesian viewpoint should be taken in interpreting the results of these causality tests (Granger, 1969). What this means in the context of our problem is that a multivariate regression formulation about factors impacting mortality rates in the US, for example, is to capture a period following the period used to test for causality. Otherwise, one may end up in a situation where the presence of Granger causality based on test results coincides with no correlation between the variables when multivariate regression is estimated if only contemporaneous values of the regressors are considered. Moreover, the issue of multicollinearity becomes critical in such situations, as it is often the case in a large and complex model. Careful selection of regressors is necessary as some of them could be correlated to a significant enough degree to deem estimated coefficients both inconsistent and inefficient. Thus

variables selection, and in turn, model specification become critically important to ensure validity of the estimated model.

The important takeaway from this paper is that property damages due to climate change-caused natural hazards help predict mortality rates of old age and middle age population in the United States. This result is not only important to the life insurance industry but to the property and casualty industry too. The common factor in both cases is that climate change-induced hazards lead to property damages which, in turn, Granger cause mortality rates. Thus it is possible to see how joint efforts could help alleviate some of the pressures on human health and mortality rates by creating a portfolio or umbrella of climate change-related policies. Incorporating property damages into mortality rate models or indices in a statistically sound way is a challenging task and a topic for our further research.

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