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Regression Analysis of Financial Loss Due to Hurricane Harvey

Frederick Chung and Baabak Ashuri, Ph.D.
Georgia Institute of Technology
Atlanta, Georgia

The objectives of this research are to identify socioeconomic variables which are associated with financial loss per capita caused by hurricanes and to examine the strength of the relationships between the significant variables and the financial loss per capita. Since hurricane occurrences are unavoidable, researchers' interest has focused on reducing damages generated by hurricanes. To mitigate potential losses, it is important to understand which socioeconomic factors are significantly associated with the disaster loss. This research proposes a method to identify which socioeconomic variables impact the financial loss per capita caused by hurricanes and how the effects of those variables vary. An ordinary least squares regression is performed to identify variables that significantly impact financial losses. This research uses insurance claim payouts generated by Hurricane Harvey in 62 Texas counties to measure the direct financial loss per capita. Analyses results suggest that communities with the following features are relatively more vulnerable to hurricanes: located where severe storms pass through, higher rainfall amounts, lower rates of homeownership, higher percentage of mobile homes, lower employment rates, and higher female population. Findings from this research will offers insights on identifying areas susceptible to hurricane-related damages and mitigate potential disaster losses.

Keywords: Hurricane Harvey, Financial Loss, Insurance, Regression Analysis

Introduction

The United States has suffered from catastrophic hurricanes which have caused massive financial losses. A natural extreme event generally becomes a disaster when it interacts with a populated and unprepared urban environment (Burton, 2010). Not only the intensity of hurricanes but also human factors significantly affect the damage. It was found that losses due to natural disasters are increasing because more people and property are placed at more hazard-prone locations such as coastal areas (Cutter & Emrich, 2005; Pielke et al., 2008). Moreover, inflation, population growth, and growth in real wealth per capita are among the primary factors responsible for increases in hurricane related damage (Choi & Fisher, 2003).

Previous studies have qualitatively identified the factors of our living environment that would affect the financial loss and damage generated by natural disasters. Hallegatte et al. (2017) focused on evaluating the relationship between economic status and disaster damage risk. The authors argued that impoverished people are more vulnerable to disasters because they tend to live in disaster-prone locations and public funds are often used toward reducing disaster risk for relatively wealthier areas. Cutter and Emrich (2005) examined the natural hazards financial losses that occurred between 1960 and 2003 in the United States. It was found that disaster losses have increased over time. The authors claimed that disaster losses are increased not by the frequency of natural disasters, but by human factors, such as population growth and migration to more hazard-prone locations.

As important as it is to qualitatively identify factors that would affect the damage generated by natural disasters, it is also important to empirically examine the relationships between the disaster losses and the factors that influence the disaster damage. Quantitatively measuring how various factors affect disaster damages can broaden our understanding of the importance of variables. Burton (2010) investigated which socioeconomic variables impact the structure damage level due to Hurricane Katrina by conducting a multivariate regression analysis. It was found that the minority population and urban population are statistically significant in explaining the catastrophic structure damage due to Hurricane Katrina. Henry et al. (2017) examined the impact of income disparity on vulnerability to flooding through a survey investigation regarding the Thai Flood in 2011. Their analysis results showed that lower-income respondents were more likely to be inundated by the flood than higher-income respondents because of the locations of their residences and limited access to media. Previous studies have identified how multiple factors affect the damage caused by natural disasters, however, gaps in knowledge still remain regarding which factors are significantly associated with the direct financial loss due to hurricanes.

This study revisits the dataset previously analyzed by Chung and Ashuri (2022), which employed Kendall’s rank correlation analysis to examine factors associated with financial loss due to Hurricane Harvey. This research seeks to contribute a different analytical perspective by utilizing Ordinary Least Squares (OLS) regression analysis. This methodological shift is to explore the data through a lens that emphasizes the strength and nature of linear relationships between variables, offering a complementary view to the non-parametric approach taken by Chung and Ashuri (2022). OLS regression is particularly adept at providing estimations of the magnitude of impacts that Kendall's rank correlation does not focus on. By employing this technique, this study aims to provide insights into the quantitative significance of various factors, potentially leading to more direct policy implications.

The objectives of this research are to identify variables that are associated with the financial loss per capita caused by hurricanes and to examine the effects of explanatory variables to the financial loss per capita. This research included not only socioeconomic variables but also hurricane and geological variables as the explanatory variables to represent the complex nature of financial losses generated by hurricanes. The findings of this research will improve our understanding of socioeconomic variables that significantly affect the financial loss per capita due to hurricanes and help to identify communities that are more vulnerable to hurricanes than the others.

Methods

One of the crucial steps in this analysis was to select variables that would be analyzed. The variables were selected based on findings of previous research and the availability of access to data. The hurricane, geological, and socioeconomic variables were selected to depict the complex nature of financial loss generated by hurricanes. This research focused on utilizing empirical data collected from Hurricane Harvey in 62 Texas counties and the explanatory variables of the corresponding counties. Hurricane Harvey was a catastrophic storm that resulted in severe damage in Texas and Louisiana in August 2017 (National Weather Service, 2017). The path of Hurricane Harvey and its windspeed categories are shown in Figure 1(a). The windspeeds of the hurricane were categorized into tropical storm and hurricane storm categories, following the National Oceanic and Atmospheric Administration (NOAA) (2021)'s guidelines. As shown in the figure, the severity of Hurricane Harvey varied depending on the location. For this reason, the storm category was used as one of the explanatory variables.

(a) (b)

Figure 1. Areas affected by Hurricane Harvey: (a) severe storm categories; (b) rainfall totals (inches) (National Weather Service 2017; NOAA 2017)

Figure 1(b) shows the rainfall amount from Hurricane Harvey in different areas. According to the figure, the total amounts of rainfall were different from region to region: hence, it would be reasonable to assume that different areas might have experienced flood damage of different sizes. Thus, the rainfall amount was selected as one of the explanatory variables. The highest storm category and rainfall amount that each county experienced were used for values of explanatory variables to reflect the impacts that were brought by the weather condition. To calculate the rainfall amount each county experienced, the mean values of rainfall amount ranges indicated in Figure 1(b) were used. Furthermore, flood damages were not only caused by the rainfall amount but also were generated by storm surges (NOAA, 2017). Therefore, geographic elevation was considered as a variable in analyses. This research used the mean elevation for each county which was calculated from elevation data retrieved from the United States Geological Survey (USGS) (USGS, 2008). The elevations of unit cells, size of 500 meters in width and height, were retrieved from the data. Then, the mean elevations of counties were calculated by taking the average elevations of unit cells contained in each county and converting the unit of elevation from meters to feet. Additionally, as stated earlier, socioeconomic factors were utilized as explanatory variables. This research selected 20 explanatory variables to explore which of these variables affect the financial loss per capita. The selected variables and their justifications for selection are listed below. The data of explanatory variables were collected from the NOAA, U.S. Census Bureau, USGS, and Federal Emergency Management Agency (FEMA) (NOAA, 2017; U.S. Census Bureau, 2018; USGS, 2008; FEMA, 2020)

1. Storm Category (0 to 4): This variable represents the highest storm category that each county experienced. The experienced wind speeds during Hurricane Harvey were different from location to location. (NOAA, 2017). The windspeeds of the hurricane were categorized into tropical storm and hurricane storm categories as they were defined by NOAA. The storm category gets higher as windspeed gets higher, and the higher windspeed tends to generate more critical damages (NOAA, 2021).
2. Rainfall Amount (inches): The highest rainfall amount that each county experienced was used for this variable. The rainfall amounts from Hurricane Harvey differed depending on the location (NOAA, 2017). The areas with higher rainfall amounts would be relatively more vulnerable to flooding than other areas.
3. Elevation (feet): This variable indicates the mean elevation of each county that was calculated from the data collected from USGS. The flood damages were also generated by the storm surge (NOAA, 2017). The areas near shore are generally located at lower

elevations than the areas away from shore. The areas with lower elevations tend to be more exposed to storm surges generated by hurricanes (Frazier et al., 2013).

4. Elderly Population Living Alone (%): This variable describes the percent population of over 65 living alone. The elderly population is more vulnerable to disasters due to their physical health (Morrow, 2008). They experience more difficulties in preparing for hurricanes and reacting to emergent situations.
5. Female Population (%): Females frequently have more difficulties when reacting to disasters due to dependency on employment sectors, lower wages, and family care responsibilities (Hummell et al., 2016)
6. Single Parent with Dependent (%): This variable expresses the percentage of families headed by a single parent. Families headed by a single parent would have a lack of sufficient economic and human resources to prepare for natural disasters (Morrow, 1999).
7. Education Level (%): This variable represents the percent population with a high school or higher degree. Having sufficient education to understand the issues associated with disaster leads to better decision-making (Norris et al., 2008).
8. Healthcare Coverage (%): This variable refers to the percent population with healthcare insurance. Having high percentages of residents with healthcare insurance may demonstrate higher levels of disaster resilience (Cutter et al., 2010).
9. Minority Population (%): This variable indicates the percent population of minorities. Different lifestyles and habits of various races may affect their resilience against disasters (Burton 2010). Minorities tend to be vulnerable to environmental hazards because of cultural differences, social, economic, and political marginalization, and the lack of access to resources (Cutter et al., 2003).
10. Households with Limited English (%): This variable describes the percent of households that speak limited English. Previous research found that immigrants with limited English-speaking ability can be more vulnerable to disasters (Cutter et al. 2003). Those who speak limited English are likely to have difficulties in understanding warnings and seeking information (Morrow, 2008).
11. Homeownership (%): This variable represents the percentage of homes that are occupied by the owner. Homeownership is an important component when measuring vulnerability (Cutter et al., 2003). Homeownership is used to measure the economic stability of communities, which influences resilience to disasters (Cutter et al., 2010).
12. Median Housing Value ($): The quality of housing is another significant component of vulnerability (Cutter et al., 2003). Expensive houses can be more durable against disasters. On the other hand, expensive houses may require higher costs to repair.
13. Median Income ($): The communities with higher income would have more spare resources to increase the resilience level of their communities (Kahn, 2005). However, higher income communities may have higher financial losses due to the high price of properties.
14. Employment Rate (%): The employment rate is one of the indications to measure economic stability (Cutter et al., 2010). Employment opportunities are vital to creating the resource for building resilient communities to disasters (Norris et al., 2008).
15. Old Housings (%): This variable represents the percentage of housing built before 1970. As buildings age, they are more likely to cause higher insurance claims for wind damage (Kim et al., 2016). Moreover, the first windstorm building codes developed by the Texas Windstorm Insurance Association took effect in 1971 (Foundation Performance Association, 2018). The houses built prior to the windstorm building codes would be more vulnerable to severe storms (Pielke et al., 2005). Due to the data availability, this study used the percentage of housing built before 1970 instead of the ones built before 1971.
16. Severe Housing Condition (%): This variable indicates the combined percentage of housings without plumbing and housings without a kitchen. The condition of housing may affect their

vulnerability to disasters. Due to the limited available data, an assumption was made that housings without a kitchen or plumbing could be in unstable conditions.

17. Mobile Homes (%): The quality of residential construction affects potential losses. Mobile homes can be damaged easily, and therefore they also can be more vulnerable to disasters (Cutter, 2003).
18. Renter-Occupied Housings (%): Renters have difficulties in preparing for disasters because they lack control over the buildings in which they live, including whether the buildings are structurally sound and have shutters or wind protection (Morrow, 1999). Moreover, people who rent housing tend to not have the financial resources to own homes (Cutter et al., 2003).
19. No Vehicle Owned (%): Lack of a vehicle would cause difficulty in preparing for the upcoming disasters and reacting to emergent situations.
20. Previous Disaster Experience (Count): Disaster experiences enhance communities' preparation for disasters in the future (Cutter et al. 2010). This information was collected by counting the number of disaster declarations (severe storm, hurricane, and flood) made by FEMA in the past 10 years after the occurrence of Hurricane Harvey.

After the experience of Hurricane Harvey, the Texas Department of Insurance (TDI) issued a Hurricane Harvey data call to collect data from insurers about the financial impact of the hurricane and to provide the data to policymakers and public officials (TDI, 2018). The data were collected from 650 companies which represented more than 99 percent of the property and automobile markets in Texas (TDI, 2018). The paid losses and claim reserves (expected future payment) caused by Hurricane Harvey in 62 Texas counties were provided in the report. The total loss was expected to be about $19.6 billion. This research used the data of estimated total payouts by the county to calculate the financial loss per capita as the dependent variable in the analyses. The financial loss per capita for each county was calculated by dividing the sum of paid losses and claim reserves in each county by the population of each county. The financial loss used in this research is limited in that it did not include the losses that might not have been covered by insurance. Moreover, the financial loss used in this research does not cover indirect loss such as the induced economic loss due to disruptions of economic activities. The descriptive statistics of the dependent variable are shown in Table 1.

Table 1

Descriptive statistics of financial loss per capita

Dependent Variable	Mean	Minimum	Maximum	Standard Deviation
Financial Loss Per Capita ($)	1780.17	3.61	36993.33	5057.20

The multicollinearity between independent variables was examined. Multicollinearity exists among the explanatory variables in a multivariate regression when those variables are related to each other (Bowerman et al., 2005). A substantial degree of multicollinearity can inflate the variances of affected variables and generate less certain results among the variables. The Variance Inflation Factor (VIF) was calculated to measure the multicollinearity among the variables. The VIF allows responders to interpret how much of each explanatory variable can be explained by the other variables. Bowerman et al. (2005) explained that the multicollinearity between explanatory variables is considered severe if the VIF is larger than 10. From the evaluation, the educational level and renter-occupied housing variables were excluded from the analysis. Furthermore, the dependent variable was positively skewed with a skewness value of 5.78. To satisfy the regression's general assumptions, the dependent variable was logarithmically transformed. Additionally, The data analyses were conducted with standardized variables. Standardizing allows to adjust each variable's scale and unit into a common scale and unit (Karlaftis et al., 2010). The magnitudes of standardized coefficients can be compared to identify the importance of explanatory variables to explain the dependent variable.

Results and Discussion

The OLS regression was conducted on the 62 counties in Texas to examine the relationship between explanatory variables and financial loss per capita caused by Hurricane Harvey. The analysis was performed from the MATLAB software (The MathWorks Inc., 2021). The model generated from the OLS regression is defined by Equation (2) below.

$$log(Loss\ Per\ Capita) = a_0 + a_1[Storm\ Category] + a_2[Rainfall\ Amount] + a_3[Homewonership] + a_4[\ Mobile\ Homes] + a_5[Employment\ Rate] + a_6[\ Female\ Population] \quad (1)$$

where, a_0 is a constant and a_i is a coefficient of the i-th explanatory variable (Karlaftis et al., 2010). Because the dependent variable was logarithmically transformed and the variables were standardized, the log of the dependent variable changes in a_i standard deviation when the i-th variable is changed by one standard deviation. The adjusted R-squared value of 0.81 was achieved from the OLS regression model. Based on the adjusted R-squared values, OLS regression explain a high proportion of variance for the dependent variable. The coefficients of significant variables found from the OLS regression are presented in Table 2. The residual plots in Figure 2 indicate that the regression model assumptions are satisfied. Storm category, rainfall amount, mobile homes, and female population have positive relationships with the financial loss per capita. On the other hand, homeownership and employment rate have negative relationships with the financial loss per capita. The order of coefficient magnitude among variables is: (1) storm category, (2) rainfall amount, (3) homeownership, (4) mobile homes, (5) employment rate, and (6) female population.

Table 2

Coefficients of significant variables estimated from the ordinary least squares regression model

Significant Variables	Coefficient	Standard Error	P-Value	VIF
Storm Category	0.762	0.089	< 0.001	2.584
Rainfall Amount	0.573	0.105	< 0.001	3.593
Homeownership	-0.271	0.121	0.031	4.766
Mobile Homes	0.255	0.121	0.041	4.774
Employment Rate	-0.230	0.107	0.037	3.683
Female Population	0.222	0.066	0.002	1.408

(a) (b)

Figure 2. Residual plots: (a) QQ plot; (b) scatter plot

The financial loss per capita increases as the storm category gets higher. The storm category had the largest influence on the dependent variable among the identified significant variables. As described in Figure 1(a), the wind speed of the hurricane rises as the category of the storm gets higher. It would be more likely for higher speed wind to cause more financial loss. The NOAA (2021) explained that the types of damage are expected to be more severe as the storm category becomes higher. Kim et al. (2016) also found that the value of commercial building damage loss divided by the building's appraised value increased as the wind speed of the hurricane increased.

The areas that experience a higher rainfall amount would have higher financial loss per capita. Similar to the storm category, the disaster loss would increase as the rainfall amount increases. The NOAA (2017) reported that Hurricane Harvey brought catastrophic flooding damage. This result is in concurrence with previous research that precipitation of hurricanes clearly affects losses from severe weather events (Choi and Fisher, 2003).

The financial loss per capita decreases as the homeownership increases. The ownership of housing is an important factor affecting vulnerability (Cutter et al., 2003). Homeownership is one of the components that measure the economic stability of communities, which influences the resilience to disasters (Cutter et al., 2010). People who own houses are more likely to have financial stability than those who do not own houses. They would have more spare resources to live in a safer environment. Furthermore, homeowners have more chances to live in a safer environment because they have more control over repairing and retrofitting their dwellings to build more durable houses. On the other hand, people who live in rented houses have difficulties in preparing for disasters due to a lack of control over the buildings in which they live, including whether the buildings are structurally sound and have shutters or wind protection (Morrow, 1999).

The areas with a high percentage of mobile homes have relatively higher financial loss per capita. The quality of residential construction affects the financial losses. Mobile homes are easily destroyed and susceptible to catastrophic loss during an event (Cutter, 2003; Cutter et al., 2010). The vulnerability of mobile homes was also found in a previous hurricane disaster. In 1992, Hurricane Andrew destroyed about 90 percent of all mobile homes in south Dade County, Florida (Pacquette, 2017). Moreover, mobile homes are popular and a common form of residence for low-income populations in rural areas (Aman and Yarnal, 2009). Income is an important resource for developing the ability to absorb and respond to disasters (Kahn, 2005). Mobile home residents are more likely to suffer from disasters because their incomes are not enough to provide proper protection for them.

As the employment rate increases, the financial loss per capita decreases. Previous studies found that a high employment rate adds stability to community resilience to disasters. Norris et al. (2008) emphasized that economic development is one of the key drivers that help communities to be prepared for disasters. Employment opportunities are essential for the economy to develop and to create the resource for building resilient communities to disasters (Norris et al., 2008). Cutter et al. (2010) also suggested considering the economic vitality of communities when measuring the resilience to natural disasters. The authors further stated that a higher employment rate enhances economic resilience, which in turn helps to generate resources required for building a stronger environment to protect against disasters.

The financial loss per capita due to hurricanes increases as the female population increases. Females tend to be more vulnerable to disasters than males because of their biological characteristics, psychological features, and social roles within society (Chen et al., 2013). Hummell et al. (2016) stated that females have difficulties in reacting to disasters due to family care responsibilities.

Conclusions

The OLS regression explained a high proportion of the variance for a dependent variable. Among twenty variables that were considered to affect financial loss due to hurricanes, six variables were found to be significant from the OLS regression model for explaining variations of financial loss per capita due to Hurricane Harvey. Results suggest that communities with the following features are relatively more vulnerable to hurricanes: being located where severe storms pass through, experiencing higher rainfall amounts, having lower homeownership, having a higher percentage of mobile homes, having lower employment rates, and having a higher percentage of females. Overall, financial loss per capita generated by Hurricane Harvey is identified to be highly impacted by the properties of hurricanes. Although significant socioeconomic variables have less impact than hurricane properties, they have a considerable amount of influence on financial loss per capita.

This research contributes to the body of knowledge in understanding which socioeconomic variables affect the financial loss caused by hurricanes and how the effects of variables vary. However, the findings from this research may be applicable for only massive hurricanes because the results are derived from the empirical data collected from the event of Hurricane Harvey in the 62 Texas counties. To reduce biases and create more general results, it would be necessary to perform assessments using other hurricane events in the studied area. Furthermore, including more factors that would affect financial loss per capita may improve the analysis results and broaden our understanding of which variables significantly affect the financial loss per capita. It is important to keep analyzing hurricane empirical data to help government and policymakers to find areas that are vulnerable to hurricanes and build communities that can better withstand the potential disaster loss.

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