Forensic Investigations of Hurricane-induced Property Damages:
A Spatial Econometric Analysis

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Abstract: In this paper we examine property damages resulting from a major hurricane using a household survey conducted in areas affected by Hurricane Sandy. We employ spatial econometric tools to investigate the impact of hurricane and home structural characteristics on damages and associated spatial dependencies. To control for the intensity of hurricane and assess the hazard exposure on the property damage, we generate multiple hurricane intensity measures at the census-tract level using the HAZUS-MH analysis tool, which provides exogenous variation for the survey data analysis. Our analysis offers forensic evidence demonstrating that both the extent of hurricane exposure and structural vulnerability significantly contribute to property damages. Moreover, insurance coverage effectively mitigates losses for households affected by hurricanes. A better understanding of the underlying causes of the increasing disaster losses can provide individuals, policymakers, and insurance agencies with key insights to mitigate the risks of future hurricanes. We also emphasize the crucial need to address socio-economic vulnerability to enhance the effectiveness of disaster risk reduction strategies and promote resilience in coastal communities.

Keywords: Property Damage, Spatial Econometrics Analysis, Forensic Investigations of Disasters (FORIN), Insurance, Hazard Mitigation

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1. INTRODUCTION

Large-scale disasters like hurricanes impose massive economic and social stress on coastal residents and communities worldwide. In recent years, the United States has experienced significant economic losses associated with hurricanes, with 2021 setting a new record of 20 billion-dollar weather and climate disasters. The cumulative estimates for these events exceeded $145 billion, marking it the third most expensive year in recorded history, trailing behind 2017 ($306 billion) and 2005 ($215 billion) (NOAA, 2022). These catastrophic hurricane events, characterized by high winds, storm surge, and flooding, lead to fatalities among coastal residents and cause tremendous damage to their properties. The impact of hurricanes on property loss is further magnified by the effects of climate change, which contribute to more frequent and intense extreme weather events, increasing the vulnerability of properties and communities. The expanding urban population and infrastructure development in hazard-prone areas further compound the potential for property loss. According to the new Hurricane Risk Report (CoreLogic, 2023), more than 32 million homes on the Atlantic and Gulf coasts, with a combined value of over $11 trillion, are at risk of hurricane wind damage.

Several studies have examined the impact of natural disasters on property loss in terms of property values. Using a difference-in-difference approach, Hallstrom and Smith (2005) illustrated a declining trend in property values due to hurricane risks. Zhang (2016) utilized spatial quantile regression to examine the influence of flood hazards and found a negative impact on property values for those located within floodplains. Simmons and Sutter (2007) analyzed data on property sales in tornado-prone areas and discovered that properties equipped with internal shelters had a positive impact on their value, highlighting the importance of protective measures. Bui et al. (2014) conducted a comprehensive analysis of three disaster types (storms, floods, and droughts) and found that all of them have adverse effects on household welfare and property values. Similarly, studies on earthquakes, tornadoes, and wildfires have consistently indicated a negative effect on housing values (Donadelli et al., 2020; Mueller et al., 2009; Murdoch et al., 1993).

Fronstin and Holtmann (1994) conducted one of the earliest studies that specifically examined the determinants of property damage caused by Hurricane Andrew. Their findings revealed that stronger winds and newer homes were associated with greater damage to properties. Huang et al. (2008) studied the 1998 flooding in China and found that property loss accounted for a significant portion (57.38%) of the total economic loss. De Silva et al. (2008) explored the spatial dependence among housing damages caused by tornadoes and identified spatial correlations within the affected areas. Similarly, Pan (2015) focused on understanding the spatial distribution of property damage due to Hurricane Ike and identified property losses over a widely extended area, illustrating the extensive reach of hurricane-related property damage. Meng and Mozumder (2021) examined various factors, including wind exposure, duration of utility service disruptions, and socio-economic characteristics, to explain property damages and recovery performance in the aftermath of Hurricane Sandy. Davlasheridze et al. (2017) concluded that economic exposure and socio-economic vulnerability were the primary drivers of property losses due to hurricanes. They also evaluated the effectiveness of FEMA expenditures on hurricane-induced property losses, shedding light on adaptation and mitigation strategies to reduce future damages.

While these studies have collectively enhanced our understanding of the determinants, spatial patterns, and economic implications of property damage caused by natural disasters, there is still limited knowledge about the process and root causes of disaster damage (Fraser et al., 2016). It is crucial to move beyond merely understanding current capacities, vulnerabilities, and post-disaster conditions and delve into why risks and vulnerabilities arise in the first place (German Committee for Disaster Reduction, 2012). In addressing this gap, the Forensic Investigations of Disasters (FORIN) approach offers a valuable conceptual framework for conducting root cause analysis. This approach emphasizes the need for research that deepens our systematic understanding of the complex process and underlying causes of the growing trend of disaster losses (Burton, 2010; Oliver-Smith et al., 2016).

In this study, we present an empirical analysis of storm-induced property damage utilizing the FORIN framework. We focus on Hurricane Sandy as a case study. Hurricane Sandy, also known as Superstorm Sandy, was a powerful and devastating hurricane that struck the northeastern United States in late October 2012. This powerful hurricane caused extensive damage to properties and had a profound impact on the wellbeing of affected communities. Our analysis aims to investigate both aggregated and disaggregated property damage caused by Hurricane Sandy while also considering the potential spatial dependence of these damages. We utilize survey data collected from affected communities to investigate various factors that contribute to property damage. These factors include not only the physical exposure to the hurricane but also the structural vulnerability of housing, incorporating a range of housing-related characteristics. Additionally, we examine the property loss after insurance coverage and explore socio-economic vulnerabilities that can influence the decision to purchase insurance as a means to effectively mitigate damage.

Hurricane mitigation has proven to be an effective strategy for reducing property loss (Botzen et al. 2019; Davlasheridze et al. 2017; Shreve and Kelman 2014), and many households have undertaken different mitigation measures. In addition to structural mitigation strategies, such as shutter installment or roof reinforcement, nonstructural mitigation measures like insurance have gained significant attention (Sigren et al., 2018). Against this backdrop, understanding the underlying causes of property damage related to hurricanes and home structural characteristics at the household level is crucial for developing effective strategies to minimize future losses. It is also essential to evaluate the effectiveness of insurance coverage in mitigating disaster losses. Our study contributes to the empirical knowledge base of forensic disaster analysis and potentially provides insights to enhance disaster preparedness and promote mitigation strategies. It also highlights the household benefit of appropriate insurance coverage to safeguard their properties against future damages.

2. CONCEPTUAL FRAMEWORK

In an effort to contribute to the goals and expected outcome of the Sendai Framework for Disaster Risk Reduction 2015–2030, the IRDR (Integrated Research on Disaster Risk) has developed a conceptual framework and research guide, known as Forensic Investigations of Disasters (FORIN), to enhance our understanding of disasters (Oliver-Smith et al., 2016). The term “forensic” is used to describe an investigative approach that seeks to uncover the underlying causes of increasing disaster losses. It involves identifying social features and institutional factors that contribute to the development of risk drivers, which are ultimately manifested in patterns of vulnerability and exposure. When these factors interact with natural or technological hazards, they can result in the occurrence of a disaster.

The FORIN framework highlights the need for new research paradigm that shifts the focus from analyzing the impact of exogenous events to delving into the cause of endogenous risks, and identifies effective policies and practices for managing disaster risks. Typically, the FORIN approach begins by investigating physical events that trigger disasters. Accordingly, we can explore questions such as the scale or intensity of the triggering event and whether subsequent additional events followed (e.g., hurricanes succeeded by flooding). The next essential step involves assessing the vulnerability and exposure to varying disaster intensities, including the hazard-prone locations and types of infrastructure. In addition, analyzing the social and economic structure and the institutional and governance elements within exposed communities is essential. For instance, understanding the availability of resource access pathways that facilitate an adequate response to disastrous events can be an important research question to investigate. The FORIN approach specifically recommended researching the role of insurance in the context of the social and economic structure, as well as the availability and requirements of insurance coverage under the institutional elements. By exploring these research questions, we can establish a better understanding of damage and loss, identify risk drivers, and inform evidence-based policy decisions to enhance disaster risk reduction efforts.

Yuan and Liu (2018) provided an overview of recent studies that applied the FORIN framework, including the examination of infrastructure damages caused by a typhoon in Taiwan (Huang et al., 2013), the investigation of physical damages resulting from the 2012 Umbria floods (Menoni et al., 2016), the assessment of the physical, social, and economic impacts of recurrent climate change events in Metro Manila (Gotangco et al., 2013), and multiple case studies focusing on hurricanes in the United States, such as Hurricane Sandy (Mühr et al., 2012), Hurricane Harvey (Mühr et al., 2017a), and Hurricane Irma (Mühr et al., 2017b). The authors also identified a common issue related to data availability and reliability in these studies. Particularly, these studies exploring the causes of damages were conducted at an aggregated scale rather than an individual/household scale. In response to this limitation, Yuan and Liu (2018) presented a case study that investigated the damages to exposed evacuees during Hurricane Harvey using crowdsourcing data. Schröter et al. (2018) also emphasized the importance of reliable empirical data for identifying the fundamental causes of disasters. They proposed the use of social media data and household surveys as useful approaches to address this data challenge.

In this study we utilize the FORIN framework and employ econometric tools to analyze highly granular disaster loss data at the household level. By using a carefully designed survey instrument, we build a rich geospatial database that captures information regarding damages, building types and structural features, and socio-economic characteristics, which enables us to perform disaster impact analysis with forensic evidence. Specifically, the survey collected disaggregated information of loss and damages, including losses with and without insurance coverage, as well as damages categorized as exterior and interior. These types of disaggregated data provide a vivid pathway to understanding the mechanisms driving the extent of damages and losses triggered by a hurricane event, offering forensic evidence at a very granular scale.

Moreover, with the availability of geo-location data, we can integrate the survey data with relevant locational and hazard characteristics, such as wind speed, wind direction, flood zone, and distance from coast. Through spatial econometric analysis using this unique geospatial database, we are able to uncover the roles of wind and flood factors, and their interactions with structural characteristics, in shaping the nature and extent of damages. These analyses provide valuable forensic evidence as they establish the causal mechanisms that explain the wide range of damages and the intervening conditions that mitigate them. In our case, how wind direction, wind intensity and flood factors drive interior and exterior damage indicate some of these underlying mechanisms. Furthermore, we differentiate the types and extent of damages for attached and detached homes and investigate the role of building age and the number of doors and windows on damages, providing additional support for forensic evidence.

3. MODEL AND SURVEY DATA

To investigate the effects of hurricane characteristics and home structural characteristics at the household level, we estimate the following model, expressed as:

$$D = f\ (H, S) \tag{1}$$

where D represents the property damage as well as the uninsured property losses, measured in dollars, caused by Hurricane Sandy; H is a vector of various hurricane characteristics, and S is a vector of different home structural characteristics.

The household survey was designed and conducted by researchers at Florida International University (FIU) in July 2013. The Gfk Group, a prominent survey administration company known for its KnowledgePanel, was contracted to carry out the survey online. The KnowledgePanel consists of individuals who are randomly recruited through probability-based sampling methods. The target population included households affected by Hurricane Sandy in ten states located in the Northeastern United States[1]. To ensure accuracy and relevance, respondents were first asked whether they had been impacted by Hurricane Sandy before

[1] The ten states are New Jersey, New York, Connecticut, Pennsylvania, Maryland, Massachusetts, Rhode Island, Delaware, Virginia, and West Virginia.

proceeding with the survey, and then a series of questions related to property damages, housing characteristics, recovery, and socio-demographic information were asked. A total of 3,276 respondents were sampled and participated in the survey, resulting in a completion rate of 62%. After screening for qualified responses, 1,061 respondents were included in the final analysis. The average time to complete the survey was about 20 minutes.

In the survey, respondents were asked to provide information on how much (in U.S. dollars) they lost due to Hurricane Sandy. Specifically, data on five different types of property damages were collected separately, including exterior home damage, interior home damage (e.g., damage to walls, ceilings, floors, etc.), damage to furniture, damage to internal contents (e.g., computers, books, jewelry, tools, etc.), and damage to automobiles. For each damaged property reported by the respondents with positive values, we then asked how much of the loss was covered by the insurance. Figure 1 illustrates the distribution of household responses for each type of disaggregated property damage, both with and without insurance coverage. Although a significant proportion of the respondents reported zero values, we still observe a significant amount of monetary loss caused by Hurricane Sandy. The mean values and ranges for each type of property damage are $1,012 for exterior homes (ranging from 0 to $75,000), $650 for interior homes (ranging from 0 to $75,000), $168 for furniture (ranging from 0 to $30,000), $277 for internal contents (ranging from 0 to $50,000), and $228 for automobiles (ranging from 0 to $38,000). Insurance coverage played a crucial role in alleviating monetary losses for insured respondents, resulting in reduced mean values for each disaggregated damage: $517 for exterior homes, $227 for interior homes, $128 for furniture, $256 for internal contents, and $48 for automobiles.

Figure 2 provides additional descriptive statistics that focus on insurance purchases among households that reported positive property damage. A total of 275 respondents (26%) indicated exterior home damage due to Hurricane Sandy, and 39% of them had purchased insurance. For interior homes, 101 of the respondents (10%) reported damage, with 47% of them having insurance. Only 38 of the respondents (4%) reported damage to furniture, and 32% of them had insurance. About 82 of the respondents (8%) reported damage to internal contents, and 28% of them were insured. While a majority of respondents (70%) indicated having insurance to cover automobile damage, we had a smaller sample size of only 30 respondents in this category (3%).

Due to the limited number of observations available for damages to furniture, internal contents, and automobiles, our regression analysis focused on three property damage estimations: 1) total damage (*TotalDam)*, which is the sum of all five disaggregated damages; 2) exterior damage (*ExDam)*; and 3) interior damage (*InterDam)*, which is the sum of interior home damage, furniture damage, and damage to internal contents. Table 1 displays the summary statistics for the different types of property damage. The total damage has a mean value of $2,335, ranging from 0 to $135,000. Exterior damage has a mean value of $1,012, ranging from 0 to $75,000, while interior damage has a mean value of $1,095, ranging from 0 to $125,000. The corresponding total, exterior, interior property damages after deducting insurance coverage averaged $1,175, $517, and $611, respectively (refer to *TotalInsLoss*, *ExInsLoss*, and *InterInsLoss* in Table 1).

Table 1 also presents summary statistics for various hurricane and structural variables that will be examined to explain variations in property damages. These statistics were obtained from the responses collected in the household survey, including whether the home is located in a flood zone as well as the age, size, and type of the home. Among 1,061 respondents, 13% lived in a flood zone. The average age of the house was approximately 50 years. The average size of the house was about 1,874 square feet, with an average of 4 doors and 16 windows. Regarding the types of structures, we found that 65% of the surveyed respondents lived in detached single-family houses, while 13% resided in attached single-family houses. The reference group for comparison and analysis consists of respondents living in buildings with two or more apartments. Additionally, to complement the household survey, we utilized the HAZUS-MH analysis tool to generate information on hurricane wind speed, wind direction, and property location, which will be discussed in detail in the next section.

4. GIS DATA AND ANALYSIS

In addition to the survey data, we employed Geographic Information Systems (GIS) to generate a set of new explanatory variables and create maps illustrating the spatial distribution of our study sample. GIS offers numerous applications in disaster impact analysis, as well as in business and economic development analysis. It enables us to generate additional geospatial data as inputs for statistical analysis, calculate distances between relevant features, and define neighborhoods around objects (Overman, 2006). Specifically, we utilized the tightly coupled GIS program, the HAZUS-MH Hurricane Model (Vickery et al., 2006), to measure the characteristics of the hurricane. The HAZUS-MH model incorporates wind engineering principles and provides validated wind speeds and wind directions for each census tract within our surveyed areas.

Figure 3 shows the Hurricane Sandy scenario created by HAZUS-MH, illustrating the storm track and maximum sustained wind speeds categorized into three groups. The light gray polygons represent census tracts with sustained wind speeds below 64 miles per hour (mph), usually referred to as a tropical depression. The dark gray polygons represent wind speeds ranging from 64 to 74 mph, commonly known as a tropical storm. The black polygons indicate hurricane wind speeds exceeding 74 mph. By utilizing the geocoded household locations, we were able to create two dummy variables (*WS1* and *WS2*) corresponding to the census tract of residence. As shown in Table 1, 88% of the surveyed respondents experienced wind speeds corresponding to a tropical storm, while less than 5% encountered wind speeds equivalent to a Category 1 hurricane.

Furthermore, we obtained information on the wind direction at the census-tract level that each household was exposed to and created a dummy variable (*WindDir*) with a value of one if the wind direction originated from the northeast, which corresponds to the right side of Hurricane Sandy. It is known that the right side of the hurricane, relative to its direction of travel, is typically the most intense part of the storm due to the combined effect of the hurricane's wind speed and the larger atmospheric flow, known as the steering winds (NOAA, 2023). Finally, we utilized GIS to calculate the distance of each household from the coastline. The average distance was found to be approximately 14 miles. By incorporating these geophysical variables, such as wind speeds, wind direction, and distance from the coastline, we are able to understand the intensity of the hurricane impacts and gain valuable insights into the directional and spatial aspects of the hurricane that may have contributed to the observed property damages.

To explore the potential presence of spatial dependence in property damages within our study area, we conducted a series of hot spot analyses using GIS. The hot spot analysis is a spatial analytical tool used to identify clusters of high values (hot spots) and low values (cold spots) that exhibit statistical significance. Figure 4 displays the results of the hot spot analysis, revealing several consistent hot spots across various aggregated and disaggregated property damages, both with and without considering insurance coverage. The identified hot spots are mainly located near Atlantic City in New Jersey where Sandy made landfall and in areas close to the coastline in lower New York. All of these clusters are located on the right side of the storm track. Notably, we did not identify any statistically significant cold spots, suggesting that all the surveyed households were, to some extent, impacted by Hurricane Sandy, with a few concentrated clusters experiencing more severe property damage. Overall, the hot spot analysis provides compelling visual evidence of spatial dependence in property damages within our study area.

5. ECONOMETRIC SPECIFICATION

We employ a multiple regression model to estimate the effects of hurricane and home structural characteristics on property damage based on Equation (1). The econometric specification is as follows:

$$\boldsymbol{D} = \beta \boldsymbol{H} + \gamma \boldsymbol{S} + \mu \tag{2}$$

where β represents a vector of estimation coefficients for hurricane-related variables $\boldsymbol{H}$, γ represents a vector of estimation coefficients for home structure-related variables $\boldsymbol{S}$, and μ denotes the error term. We anticipate a positive sign for β, as greater exposure to hurricane impact is expected to result in higher property damages.

Given that a significant proportion of respondents reported zero damage in our survey, utilizing the Ordinary Least Squares (OLS) regression is not a suitable choice for our estimation.

Lawton et al. (2003) suggested that when the dependent variable exhibits an unusual response distribution, the use of OLS may yield inconsistent parameter estimates. Alternatively, the Tobit model is a more appropriate technique as it handles dependent variables that are clustered at a limiting value, typically zero (McDonald and Moffitt, 1980). Accordingly, we utilize the Tobit regression model for this analysis, which allows for the estimation of a latent variable. The model can be further expressed in terms of the observed variable D, expressed as:

$$\boldsymbol{D} = \begin{cases} 0, & if\ D^* \leq 0 \\ D^*, & if\ D^* > 0 \end{cases} \tag{3}$$

where ***D*** represents the reported property damages caused by Hurricane Sandy. For households with no damages, it takes a value of zero, while for households with positive damages, it corresponds to the actual dollar amount. By using the maximum likelihood regression procedure, the Tobit model appropriately considers all the information in ***D***, enabling us to examine the probability of incurring positive property damages and the changes in the probability among those who experienced damages above the zero limit (Baum et al., 2006).

Furthermore, it is important to recognize that hurricane damage to residential homes may not solely be attributed to the direct impact of the storm itself. Other factors, such as debris from other homes in the neighborhood, can also contribute to the extent of the damage. De Silva et al. (2008) referred to this phenomenon as the 'debris effect' in their study of a tornado event, where strong winds generate dust and debris that can be carried both near the source and over long distances. Similarly, in the context of a hurricane, flooding can carry debris and even wash away vehicles and other outdoor belongings, potentially leading to additional housing damage. Considering the potential influence of these factors, exploring the spatial dependence of property damages allows us to better understand the interconnected nature of the damage patterns in the study area.

As such, we also employ spatial econometric methods to examine the spatial dependence (correlation) of property damages in the areas affected by Hurricane Sandy. Spatial dependence occurs when observations in different locations exhibit significant correlations, that is, an observation in one location is influenced by observations in nearby locations. To capture this spatial relationship, a spatial weight matrix is constructed using methods such as the inverse distance method or K nearest neighbors method. Spatial correlation can occur through dependence among the dependent variables (spatial lagged dependence), among the error terms (spatial error dependence), or both (LeSage, 1999). In our empirical analysis, we employ the Spatial Autocorrelation Model (SAC) which combines the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) to deal with both spatial lagged dependence and spatial error dependence (Xu and Lee, 2015).

The specification for the Spatial Autocorrelation (SAR) Model can be written as:

$$\boldsymbol{D} = \rho W\boldsymbol{D} + \beta\boldsymbol{H} + \gamma\boldsymbol{S} + \mu \tag{4}$$

$$\mu = \lambda W\mu + \varepsilon \tag{5}$$

where $W\boldsymbol{D}$ is the spatial lagged term, and $W\mu$ is the spatial error term. The spatial weight matrix W, which is an n*n matrix, is used to identify the spatial relationship among observations. In our study, a 1061*1061 matrix is generated using the inverse-distance method based on the latitude and longitude data of each surveyed respondent. The model is estimated using maximum likelihood estimation. A statistically significant ρ coefficient indicates the presence of spatial dependence among the dependent variables, while a statistically significant λ coefficient indicates spatial dependence among the error terms.

6. ESTIMATION RESULTS

6.1. Determinants of Property Damage

Table 2 presents the estimation results from the Tobit regression models. The predicted probability of observing positive property damages and the marginal effects on positive values (right-censored observation) are presented in Table 3.

We first examine the total, exterior, and interior property damages without considering the amount of loss covered by insurance (see Models (1), (2), and (3)). The results indicate that greater hurricane exposure is associated with higher property damages. When holding other factors constant, respondents living in flood zones (*Floodzone*) experienced significantly higher property damage compared to those in non-flood zones. On average, their expected total property damage was $14,945 higher, with expected exterior and interior damages higher by $4,811 and $18,049, respectively. For respondents exposed to tropical storm-level wind scales (*WS1*), their expected damages were significantly higher: $11,168 for total damage, $3,726 for exterior home damage, and $12,826 for interior home damage. These differences are even greater when comparing those who experienced hurricane category 1 wind scales (*WS2*). The expected total, exterior, and interior home damages were significantly higher by $20,597, $8,896, and $19,777, respectively. It is worth noting that the impact of floods was stronger under a tropical storm scenario, while the impact of wind became dominant when properties were exposed to hurricane category 1 strength.

Other hurricane characteristics were also found to influence property damages for Sandy-affected respondents. Properties with wind directions originating from the northeast (*WindDir*) were associated with significantly higher expected total damage of $5,427 and higher expected exterior damage of $3,042. However, the coefficient on wind direction was found to be insignificant for interior home damage. Additionally, for every 1-mile proximity to the coastline (*Distance*), the expected total damage and interior damage increased by $104 and $173, respectively.

Regarding home structural characteristics, we found that the number of doors (*Doors*) and windows (*Windows*) had a significant impact on total property damage. Specifically, homes with a greater number of doors exhibited higher exterior and interior damages, while homes with a larger number of windows showed higher exterior damages. The type of home structure also played a vital role in determining property damage, as indicated by the statistically significant coefficients associated with detached and attached single-family houses (*DeHouse* and *AttHouse*). Compared to the reference group, respondents living in a detached single-family house were expected to experience $10,652 higher total damages, while those living in an attached single-family house were expected to face $11,110 higher total damages. Foundations are particularly vulnerable to water intrusion caused by hurricane-driven wind forces, posing a risk to the overall structure. Therefore, single-family homes with low elevations or weak foundation structures are more susceptible to damage or destruction.

Models (4), (5), and (6) from Table 2 and Table 3 present the estimation results and marginal effects of property damages excluding the amount covered by insurance, referred to as total, exterior, and interior uninsured losses. The findings revealed a strong consistency across all hurricane and home structural variables. In certain cases, information regarding the insurance coverage on the amount of damage may not be publicly available, thereby limiting researchers to solely examine property damage data without considering insurance. Our results address this limitation by providing empirical evidence that the factors contributing to property damages can also serve as reliable predictors for understanding uninsured losses.

Figure 5 presents a bar graph illustrating the marginal effect of total property damages with and without insurance coverage, using the estimated coefficients from Table 3 Model (1) and Model (4). As depicted, the average property damage for respondents is significantly lower when their property is insured against hurricane risks. This finding highlights the effectiveness of purchasing insurance as a valuable mitigation strategy for reducing monetary losses in the event of a major hurricane.

The estimation results obtained using the spatial autocorrelation Tobit model are presented in Table 4. We observed consistent results with statistically significant coefficients compared to the non-spatial Tobit model presented in Table 2. The positive and significant coefficients on hurricane characteristics reaffirm their impact on property damages. Home structural variables, including the number of doors, the number of windows, detached single-family houses, and attached single-family houses, remain statistically significant with consistent signs and magnitudes. Table 4 also provides evidence of spatial dependence or correlation in our analysis. The coefficient of the spatial lagged term, *rho*, is found to be statistically significant at the 1% level in Model (1). This suggests the presence of "debris effects" on the total aggregated property damages, indicating that properties within close proximity might have a damaging impact on each other. However, we did not find evidence of spatial dependence in the disaggregated property damages, and the coefficients of the spatial error term, *lambda*, were insignificant across all models.

It is important to note that Hurricane Sandy was a Category 1 hurricane when it made landfall in the U.S., and it lost much of its destructive wind power as it traveled inland to Pennsylvania. Therefore, it is possible that a more catastrophic hurricane event could exhibit a stronger spatial dependence, given the higher intensity of the wind and the generation of more debris. This impact could also be more pronounced in low-lying communities, such as New Orleans or Miami, where flooding can carry significant amounts of debris, including cars, and cause damage to other properties and downstream areas. As we anticipate more frequent and destructive hurricane events due to climate change in the future, analyzing and understanding the spatial dependence of property damages is critical. The identification of spatially correlated total damages resulting from Hurricane Sandy emphasizes the need for special policy attention to promote effective mitigation strategies and the sharing of hurricane risk information at the community level.

6.2 Determinants of Insurance Purchase

In order to effectively promote the idea of purchasing insurance to protect properties against hurricane and flood damages, it is essential to understand the key factors that drive heterogeneous insurance purchase behaviors among households. In Table 5, we present the location and socio-demographic information for all respondents, as well as those who reported property damage, those who had insurance coverage, and those who did not have insurance during Hurricane Sandy. Comparing the sample characteristics of all respondents in our survey, we observe that individuals who reported positive property damage tended to reside in locations closer to the coastline. Additionally, a higher proportion of these individuals lived in flood-prone areas, where the purchase of flood insurance was often required. We did not identify any significant patterns in the socio-demographic information, as hurricanes can be considered exogenous shocks that affect specific areas regardless of demographic factors.

On the other hand, there are notable differences in the socio-demographic information when comparing respondents with insurance coverage to those without. First, 21% of the insured respondents lived in flood zones, whereas only 13% of the uninsured respondents resided in such zones. The difference is more significant for flood insurance, as 19% of the insured respondents were required to have flood insurance, whereas only 6% of the uninsured respondents had this requirement[2]. While insured respondents did not necessarily live closer to the coastline, they had a higher mean number of years of residence in the same home compared to their uninsured counterparts. Another distinction can be observed in the level of concern regarding the impact of future hurricanes. Approximately 84% of the insured respondents expressed moderate to high levels of concern, while 75% of the uninsured respondents shared similar concerns. Furthermore, insured respondents were associated with higher income levels in comparison to their uninsured counterparts.

Table 6 presents the results of the logit regression models conducted to analyze insurance purchases among respondents who reported property damage. The analysis includes a total of 331 observations, with 133 insured respondents and 198 uninsured respondents. The findings

[2] Normally, flood insurance policies provide coverage for damages caused by rain and storm surge-induced flooding. However, it is important to note that the Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP) specifies certain exclusions. For instance, basement property and contents located below the lowest elevated floor are generally not covered under flood insurance policies (refer to https://www.fema.gov/flood-insurance for more information). Furthermore, to protect homes and personal belongings from wind damage, windstorm insurance is typically required.

revealed several significant predictors of insurance purchasing decisions, confirming the descriptive findings observed in Table 5. First, flood exposure emerged as the strongest predictor, indicating that respondents residing in flood zones or those required to purchase flood insurance were more likely to have insurance during Hurricane Sandy. Furthermore, the coefficients for years of residence and concern for hurricanes demonstrated a positive and statistically significant relationship with insurance purchasing. This suggests that respondents with longer years of residence, perhaps more experiences, and higher risk perceptions about the impact of future hurricanes were more likely to purchase insurance as a mitigation strategy against potential property loss. Among the socio-economic characteristics examined, income was the only significant predictor. This finding aligns with the expectation that consumption decisions are influenced by household preferences and income constraints. Wealthier respondents face fewer trade-offs and constraints in their decision-making, making them more likely to purchase insurance against disaster risks.

7. DISCUSSION

Utilizing the FORIN framework, we applied econometric tools to investigate the effects of hazard exposure, structural vulnerability, and insurance coverage on the underlying causes of storm-induced property damage. The binary variable representing hurricane wind speed emerged as the strongest predictor among the hazard intensity and exposure variables, followed by the flood zone. Properties located in areas with a greater extent of wind and/or water impact experienced more significant damage. Previous literature consistently recognized that the scale and intensity of a hurricane, often measured by maximum wind speed, are the primary drivers of loss and damage (Emanuel, 2005; Nordhaus, 2010). Cardwell and Konrad (2022) pointed out the complexity of analyzing the drivers of hurricane damage due to the interaction of multiple physical characteristics, which can vary depending on the storm and its impact location. Therefore, solely focusing on one aspect, such as maximum wind speed, may not adequately capture the overall potential hazards for damage. For example, Czajkowski and Done (2014) identified the importance of factors such as wind duration and wind direction in addition to wind speed, in their case study of two category-3 hurricanes in the U.S. However, their studies were conducted at the census tract level. This study contributes additional evidence by demonstrating the statistical significance of multiple predictors, such as flood zone, wind direction, distance from the coast, and wind speed, in determining property damage at a more disaggregated scale (at the household level).

The structural ability of the dwelling unit to withstand the destructive power of a hurricane may also contribute to the reduced severity of property damage to households (Vásquez and Mozumder, 2017). Several structural characteristics, such as age, size, elevation, and structure type, have been identified as potential determinants of hurricane damage. In particular, the age of the home was often investigated in the literature but yielded inconsistent results. Some studies have suggested that older homes and aging infrastructure are more vulnerable to wind damage (Simmons and Sutter, 2008; Gurley and Masters, 2011). Conversely, other studies found that newer homes incur higher losses than older homes (Fronstin and Holtmann, 1994; Highfield et al., 2014). These studies argue that factors such as the effectiveness of building codes over time and the growth in insurance associated with moral hazards may contribute to the results.

Interestingly, our study found no significant relationship between home age and property damage after controlling for hurricane characteristics and other structural variables. This suggests that the age of the homes may not be the primary underlying cause of disaster losses and damages. Instead, other factors, such as building design, location, structure type, retrofitting, and maintenance practices, may have a greater influence on property damage. For example, we found that the number of doors and windows significantly affected property damages. Modern homes are now designed with more and larger open spaces. It is common to see double-sized entry doors and sliding glass doors replacing regular doors in new construction. In addition to the size and design of the house, the overall structure of the house may also play a more significant role. For instance, households living in large apartment buildings with fewer doors may be less likely to experience property damage. This hypothesis is further supported by the statistically significant coefficients associated with detached and attached single-family houses in our study. These findings provide insights into the diverse factors that contribute to understanding the specific mechanisms by which structural characteristics impact property damage during natural disasters.

Moreover, households can invest in hurricane mitigation measures to protect their properties and expect a return on their investment through a likely decrease in property damages. Our findings also showed that having insurance coverage is crucial for mitigating disaster losses and promoting resilience in the face of natural disasters. It serves as a safety net for affected households by providing financial support for repairs, replacement of damaged property, and compensation for incurred losses. Javeline et al. (2022) found that coastal homeowners who are aware of insurance incentives have a higher likelihood of living in better-protected residences and taking the incentivized actions to upgrade their homes to mitigate coastal hazard risks. As such, policymakers should recognize the importance of incentivizing insurance purchase behavior and work towards creating an enabling environment that encourages residents to obtain adequate coverage.

Our findings showed that flood exposure, years of residence, and concern for hurricanes are significant factors that promote insurance purchasing behaviors, aligning with previous literature. For example, Petrolia et al. (2013) demonstrated the significant influence of residing in the Special Flood Hazard Area (SFHA) on the likelihood of holding flood insurance, particularly for mortgaged properties. This highlights the impact of mandatory purchase provisions for mortgaged homeowners, as mandated by federal law requiring participation in the National Flood Insurance Program. Similarly, Shao et al. (2017) found a positive and significant relationship between living in a flood zone and the voluntary purchase of flood insurance. Kousky (2017) examined flood insurance purchases following hurricanes and found that experiencing at least one hurricane in the previous year led to a 7.2% increase in net flood insurance purchases. Coastal residents may demonstrate higher awareness of flood risks compared to those residing in inland floodplains, as mandatory flood insurance purchase requirements primarily apply in higher-risk areas. Pompe and Rinehart (2008) observed a substantial growth in the number of insurance policies and coverage between 1992 and 2008, indicating increased concern over hurricane-induced flooding and the importance of insurance programs in assisting at-risk households living in flood zones. These results emphasize the importance of implementing policies for assisting at-risk households living in flood zones and mitigating the impacts of hurricanes through insurance programs. It is also crucial to raise public awareness and risk perceptions as an initial step toward personal preparedness and risk mitigation behaviors (Vásquez et al., 2018).

Lastly, it is important not to overlook the socio-economic vulnerability that influences the decision to have insurance coverage against future damages. Consistent with previous studies in the literature (Kunreuther et al., 1978; Landry and Jahan-Parvar, 2011; Wang et al., 2017), our findings revealed that households with higher incomes were more likely to possess insurance during Hurricane Sandy. In other words, lower-income households often face financial constraints that limit their ability to invest in preventive measures, such as retrofitting their homes or purchasing insurance. Consequently, they are more exposed to the devastating impacts of disasters, further exacerbating socio-economic inequalities. Our finding implies socio-economic vulnerability and income disparity as possible mediating causes of disaster losses. Policymakers should pay attention to this issue when implementing disaster risk reduction strategies. Strengthening social safety nets and providing contingent mitigation assistance to vulnerable communities can be instrumental in promoting resilience.

8. CONCLUSION

Due to the exacerbated impact of climate change and the growing population in coastal regions, we anticipate more frequent and devastating hurricanes in the future (Meng and Mozumder, 2023). For decades, coastal residents have experienced billions of dollars in property damage from hurricanes, primarily due to wind and wind-driven rainwater intrusion (Chatterjee et al., 2019). Therefore, it is crucial to further develop our understanding and prediction of hurricane damage. This paper analyzes the determinants of aggregated and disaggregated property damage and the potential spatial dependence of these damages using survey data from Hurricane Sandy-affected areas.

Our findings confirm that hurricanes have significant negative impacts on households, particularly through wind and flood damage. The distance of properties from the coastline and the direction of the wind are also important factors in predicting property damages. Additionally, properties with more doors and windows, as well as those in single-family houses (both attached and detached), tend to experience higher losses. Moreover, we observe evidence of spatial dependence in the aggregate property damage within the areas affected by Hurricane Sandy. This spatial dependence suggests that in addition to the direct impacts of the hurricane, losses are further amplified by damages from nearby houses (referred to as the "debris effect"). Finally, insurance coverage played a crucial role in alleviating monetary losses for affected households. Our results highlight that households facing higher hurricane risks, expressing greater concern about hurricane impacts, having more experience from longer years of residence, and possessing higher wealth are more likely to take proactive measures to mitigate risks, such as purchasing insurance coverage.

Our study contributes to the literature by examining hurricane risk in terms of specific types of property damages, as well as total property loss and uninsured property losses. Obtaining information on the insurance coverage for different types of damaged properties is challenging due to the proprietary nature of the data and the unwillingness of insurance companies to share such information. By utilizing survey responses, we are able to assess the hurricane impacts on insured and uninsured property loss at the household level and examine socio-economic factors that influence insurance holding behavior. Incorporating effective hurricane preparation strategies to minimize exposure and promote effective hurricane mitigation behaviors is critical (Pavel and Mozumder, 2019). For example, implementing preventative measures, such as installing window protections or purchasing hurricane-related insurance, can significantly reduce the likelihood of substantial property loss for households (Mozumder et al., 2015). Communities can also enhance resilience by developing realistic disaster risk mitigation plans, purchasing insurance, and sharing information (Cutter et al., 2018).

Our study also contributes to the literature by exploring the spatial dependence of property damages using spatial econometric regression. While spatial econometric analysis is widely used in various contexts, there is a surprising lack of studies specifically focusing on natural disasters, particularly hurricanes. Makridakis and Karkalakos (2020) employed a spatial hedonic model to estimate the relationship between environmental hazards and health outcomes. Zhang et al. (2019) utilized spatial lag and spatial Durbin models to demonstrate the spatial dependence and spillover effects of emitted air pollutants in China. Liu et al. (2019) conducted panel spatial Durbin models and discovered a significant spatial contagion effect on housing prices throughout China. However, none of these studies specifically investigated post-hurricane property damages, as we have done in our research. Understanding the major determinants of damages and their spatial effect in a large area caused by a major natural disaster event can provide key inputs for disaster management (De Silva et al., 2008).

Finally, our study contributes to the literature by presenting a case study that utilizes the FORIN framework and provides valuable forensic evidence to uncover the undying causes of disaster losses and damages. The nature and extent of damage caused by natural hazards are increasing in complexity. The rising intensity and frequency of hydrometeorological extreme weather events, fueled by climate change, make it more challenging than ever before, which has significant policy implications for building resilience. For instance, Vaughan (2008) described the incidents of a legal battle over whether hurricane-induced damages should be covered by home insurance or flood insurance carriers, especially when they are caused by a combination of wind and flooding. Forensic analysis of disaster damage will become increasingly useful in the coming days for resolving these nuanced types of hazard-society interactions.

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FIGURES AND TALBES

Figure 1. Survey Responses on Disaggregated Property Damages with and without Insurance

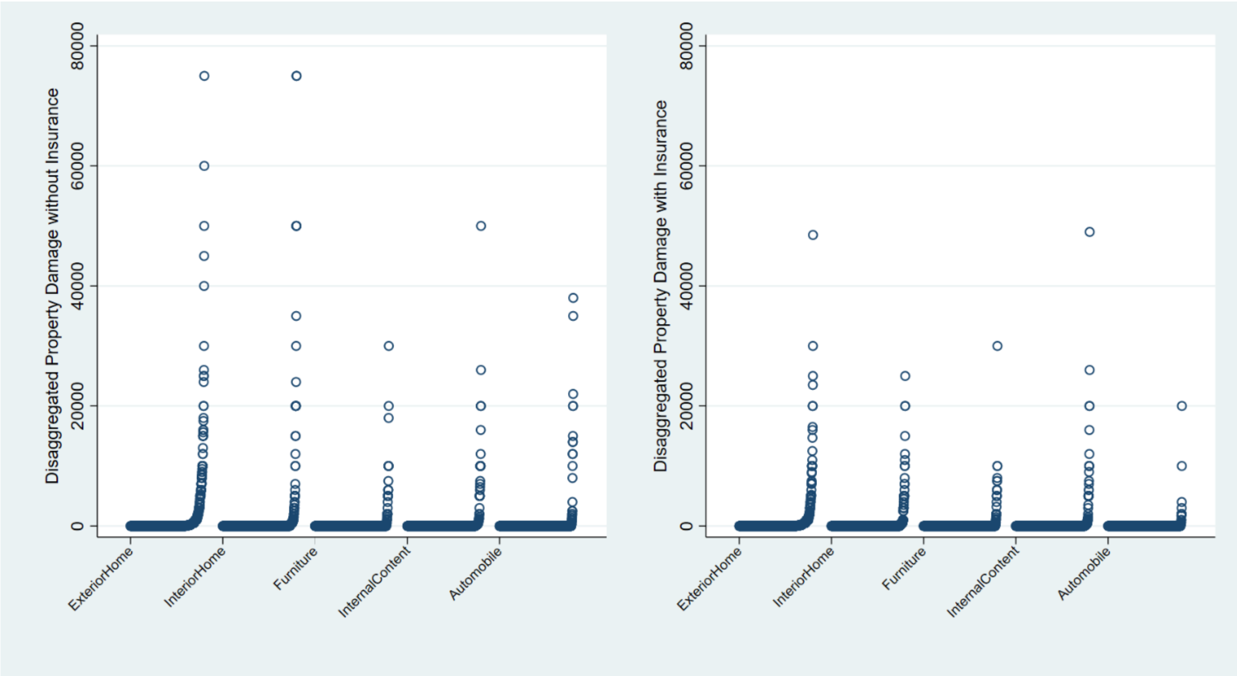


Figure 2. Insurance Status for Respondents Who Reported Property Damage

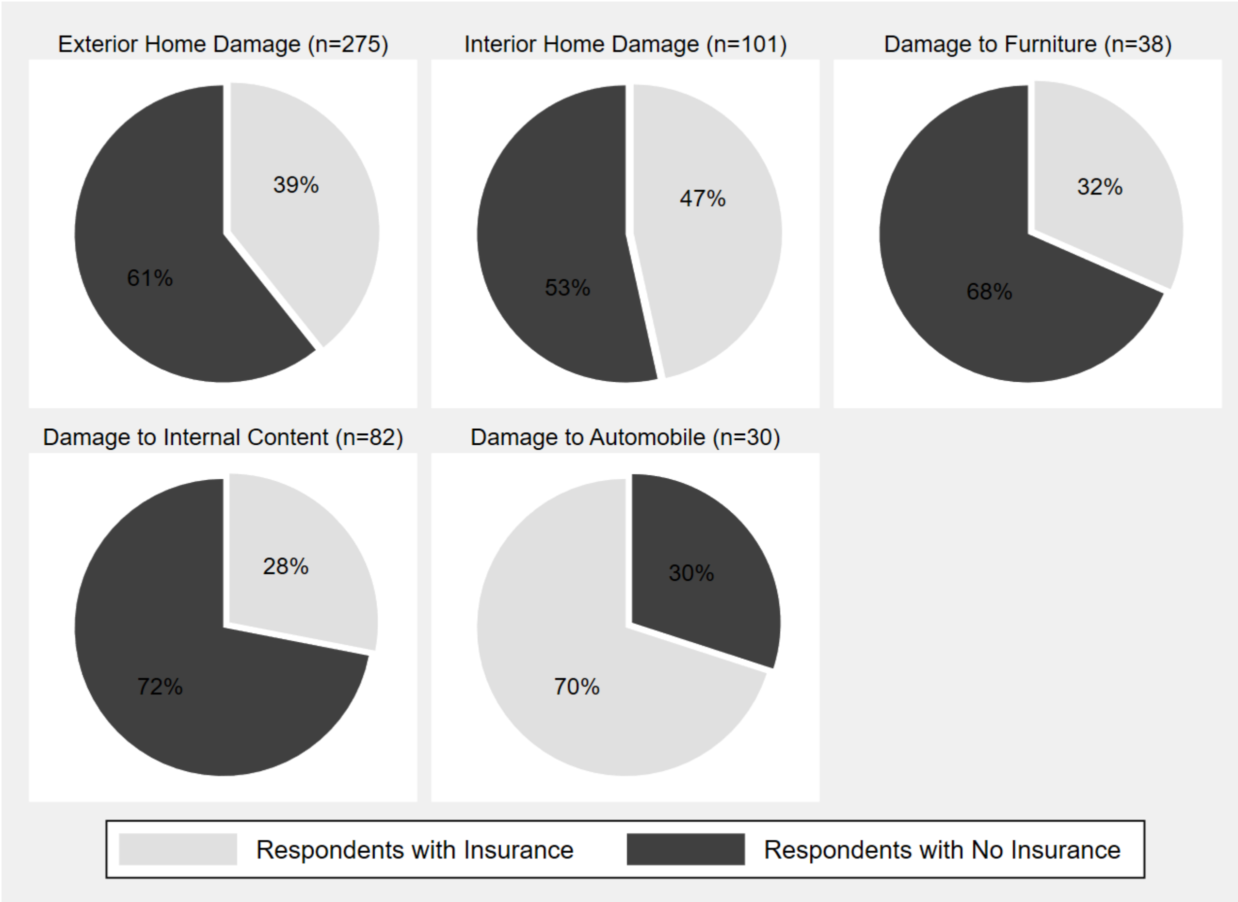
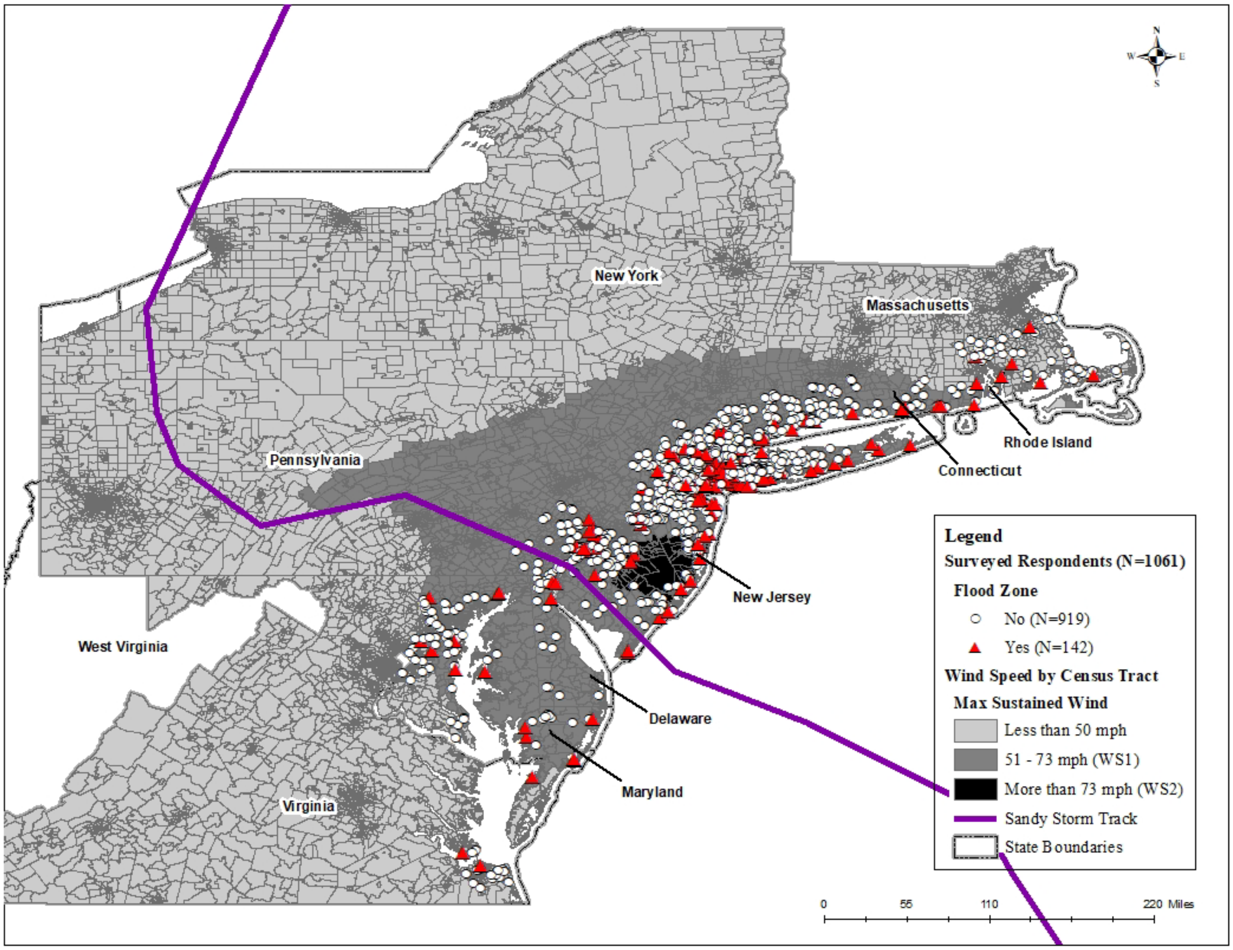


Figure 3. Hurricane Sandy's Track and Impacts on Surveyed Respondents



Note: The map shows Hurricane Sandy's path and wind speed at the census-track level for nine states. Consequently, we targeted households from these affected areas and surveyed 1061 respondents. Each respondent's location is geocoded and displayed using a triangle if lived in the flood zone and a circle if not in the flood zone.

Figure 4. Hot Spot Analysis on Reported Property Damages with and without Insurance

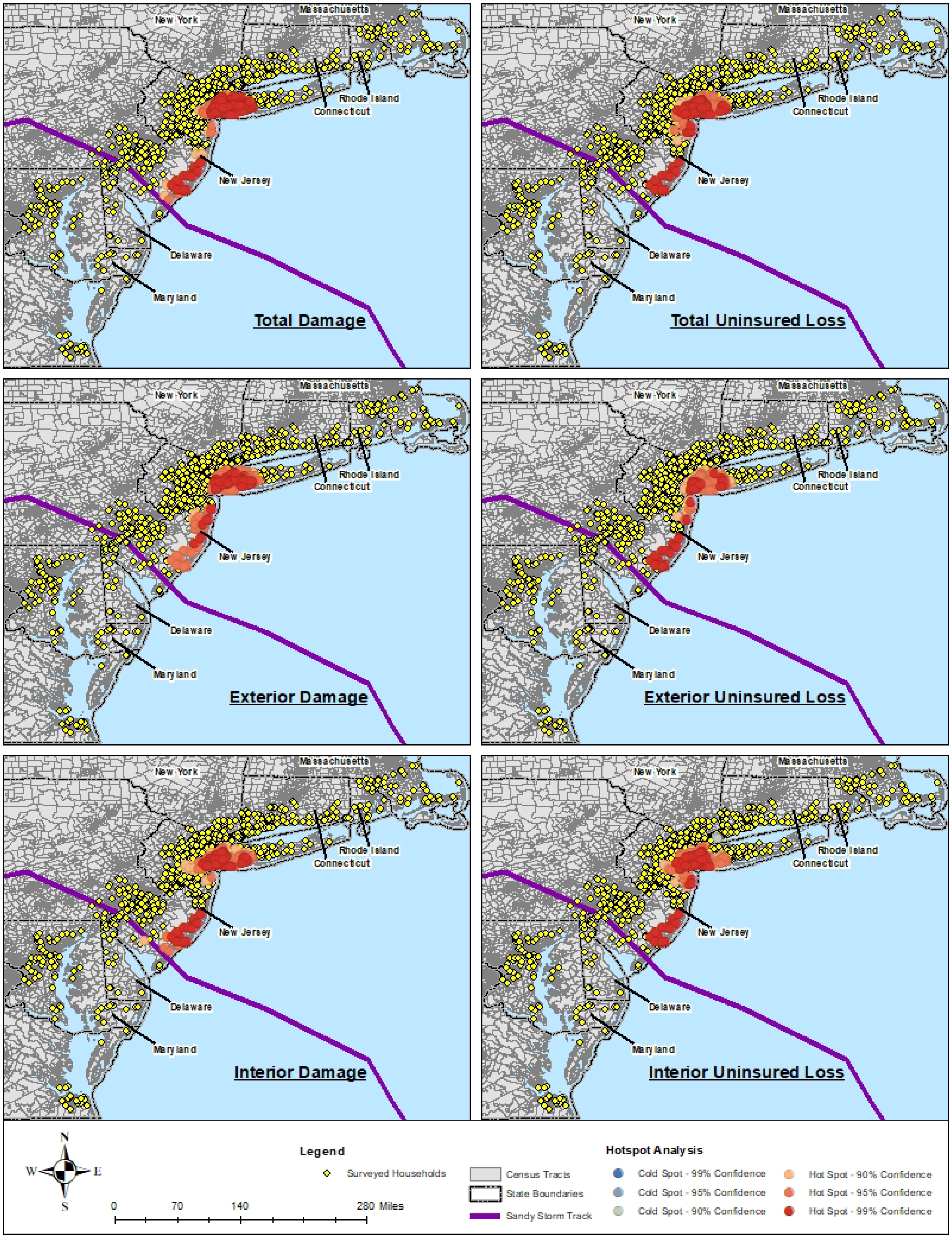


Figure 5. Marginal Effects from the Tobit Regression for Total Property Damages with and without Insurance

Table 1 Definitions and Descriptive Statistics of Variables Used in the Analysis

Name	Description	Mean	SD	Min	Max
Dependent Variables					
TotalDam	Total property loss due to Hurricane Sandy	2335.055	11037.68	0	135000
ExDam	Property loss due to exterior damages	1011.78	4724.704	0	75000
InterDam	Property loss due to interior damages	1094.811	7318.092	0	125000
TotalInsLoss	Total property loss after insurance coverage	1175.418	6271.099	0	103900
ExInsLoss	Exterior property loss after insurance coverage	516.813	2655.2	0	48500
InterInsLoss	Interior property loss after insurance coverage	610.819	4101.165	0	65000
Explanatory Variables					
Floodzone	If respondent lived in a flood zone (1=yes, 0=no)	0.134	0.341	0	1
WS1	Wind scale (1= wind speed between 50-73mph, tropical storm)	0.882	0.323	0	1
WS2	Wind scale (1= wind speed between 74-95mph, Category 1 Hurricane)	0.047	0.212	0	1
WindDir	If the wind direction is to the northeast (1=yes, 0=no)	0.77	0.421	0	1
Distance	Distance of respondent to the coast (miles)	14.293	14.343	0	66
Sqrfeet	Square foot of the property	1873.795	1696.265	50	24000
Doors	Number of doors of the property	4.115	3.570	1	32
Windows	Number of windows of the property	15.652	8.779	1	65
BldAge	Building age of the property (years)	49.685	27.755	0	142
DeHouse	If respondent lived in a detached single family house (1=yes, 0=no)	0.647	0.478	0	1
AttHouse	If respondent lived in an attached single family house (1=yes, 0=no)	0.128	0.334	0	1

Table 2 Estimation Results from the Tobit Regression Models

	(1) Total Damage	(2) Exterior Damage	(3) Interior Damage	(4) Total Damage after Insurance	(5) Exterior Damage after Insurance	(6) Interior Damage after Insurance
	(TotalDam)	*(ExDam)*	*(InterDam)*	*(TotalInsLoss)*	*(ExInsLoss)*	*(InterInsLoss)*
Floodzone	14944.6***	4810.6***	18048.8***	8233.1***	2922.5***	11168.4***
	(3492.861)	(1733.527)	(3999.509)	(2127.361)	(1069.988)	(2415.654)
WS1	11168.4***	3726.2*	12826.0**	7971.0***	2922.3**	14338.8**
	(4006.552)	(2038.503)	(6325.204)	(2710.922)	(1346.651)	(5816.683)
WS2	20597.1***	8895.7***	19777.2**	13812.7***	6106.8***	19186.8***
	(5882.041)	(3137.137)	(8003.061)	(4620.911)	(2347.804)	(7016.287)
WindDir	5426.5***	3041.7***	2748.7	2832.8**	1484.8**	1206.5
	(2054.946)	(1106.083)	(2826.869)	(1239.150)	(691.858)	(1761.115)
Distance	-103.9**	-32.10	-172.7**	-98.04***	-46.79**	-120.8**
	(51.015)	(27.717)	(79.644)	(34.216)	(18.875)	(52.102)
Sqrfeet	0.206	0.0598	0.106	0.136	0.0327	0.108
	(0.335)	(0.183)	(0.500)	(0.207)	(0.111)	(0.327)
Doors	626.2*	329.2**	1067.2**	412.6**	190.0**	724.9***
	(332.307)	(148.362)	(452.344)	(208.109)	(85.196)	(279.393)
Windows	221.9**	132.7**	114.0	149.0*	82.95*	90.60
	(108.816)	(61.013)	(134.045)	(81.565)	(42.321)	(98.392)
BldAge	28.77	7.087	12.71	6.338	1.605	10.08
	(32.114)	(16.405)	(43.282)	(20.127)	(11.200)	(27.329)
DeHouse	10651.9***	8858.5***	3797.0	5965.2***	5435.3***	1069.3
	(2985.659)	(2088.322)	(3625.149)	(1772.536)	(1270.912)	(2284.797)
AttHouse	11110.4***	7456.1***	8568.7**	7028.9***	4986.5***	4394.7
	(3303.004)	(2125.004)	(3974.867)	(2233.552)	(1447.194)	(2688.206)
Constant	-46164.6***	-25543.8***	-53846.2***	-29008.1***	-16064.2***	-40445.2***
	(7683.193)	(4856.801)	(11845.022)	(5320.265)	(3111.715)	(8612.688)
AIC	8130.9	6432.4	3693.8	6977.4	5419.9	3036.5
N	1061	1061	1061	1061	1061	1061

Robust Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 Marginal Effects from the Tobit Regression Models

	(1) Total Damage	(2) Exterior Damage	(3) Interior Damage	(4) Total Damage after Insurance	(5) Exterior Damage after Insurance	(6) Interior Damage after Insurance
	(TotalDam)	*(ExDam)*	*(InterDam)*	*(TotalInsLoss)*	*(ExInsLoss)*	*(InterInsLoss)*
Floodzone	0.213***	0.127***	0.144***	0.181***	0.117***	0.126***
WS1	0.160***	0.0981*	0.102**	0.176***	0.117**	0.162***
WS2	0.294***	0.234***	0.158***	0.304***	0.245***	0.217***
WindDir	0.0775***	0.0801***	0.0219	0.0624**	0.0595**	0.0137
Distance	-0.00148**	-0.000845	-0.00138**	-0.00216***	-0.00188***	-0.00137**
Sqrfeet	0.00000294	0.00000158	0.000000841	0.00000300	0.00000131	0.00000122
Doors	0.00894**	0.00867**	0.00850***	0.00908**	0.00762**	0.00821***
Windows	0.00317**	0.00349**	0.000908	0.00328**	0.00333**	0.00103
BldAge	0.000411	0.000187	0.000101	0.000140	0.0000644	0.000114
DeHouse	0.152***	0.233***	0.0303	0.131***	0.218***	0.0121
AttHouse	0.159***	0.196***	0.0683**	0.155***	0.200***	0.0498
	(TotalDam)	*(ExDam)*	*(InterDam)*	*(TotalInsLoss)*	*(ExInsLoss)*	*(InterInsLoss)*
Floodzone	3697.2***	1093.8***	3196.0***	1917.3***	624.7***	1860.6***
WS1	2763.0***	847.2*	2271.1**	1856.3***	624.6**	2388.8**
WS2	5095.7***	2022.5***	3502.0**	3216.7***	1305.3***	3196.4***
WindDir	1342.5***	691.6***	486.7	659.7**	317.4**	201.0
Distance	-25.71**	-7.298	-30.59**	-22.83***	-10.00**	-20.12**
Sqrfeet	0.0510	0.0136	0.0187	0.0317	0.00699	0.0180
Doors	154.9*	74.84**	189.0**	96.08**	40.61**	120.8***
Windows	54.89**	30.16**	20.19	34.69*	17.73**	15.09
BldAge	7.119	1.611	2.251	1.476	0.343	1.679
DeHouse	2635.2***	2014.1***	672.3	1389.2***	1161.8***	178.1
AttHouse	2748.7***	1695.2***	1517.3**	1636.9***	1065.8***	732.1

*First Panel: Marginal effect on the probability of observing a positive damage. Second Panel: Marginal effect on damages among the positive observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Estimation Results from the Spatial Tobit Regression Models

	(1) Total Damage	(2) Exterior Damage	(3) Interior Damage	(4) Total Damage after Insurance	(5) Exterior Damage after Insurance	(6) Interior Damage after Insurance
	(TotalDam)	*(ExDam)*	*(InterDam)*	*(TotalInsLoss)*	*(ExInsLoss)*	*(InterInsLoss)*
Floodzone	14727.6***	4818.5***	18029.2***	8187.7***	2932.0***	11174.2***
	(3475.660)	(1730.549)	(4001.427)	(2137.169)	(1069.833)	(2414.660)
WS1	10509.7***	3625.3*	12855.8**	7730.1***	2861.3**	14194.2**
	(4070.896)	(1995.756)	(6229.903)	(2685.015)	(1301.165)	(5830.505)
WS2	19533.9***	8651.8***	19814.5**	13411.7***	5974.1***	19070.2***
	(5996.772)	(3073.239)	(7906.884)	(4637.117)	(2298.181)	(6989.128)
WindDir	5168.2**	2911.0***	2506.5	2702.7**	1421.7**	1030.6
	(2122.501)	(1069.880)	(2669.115)	(1248.817)	(663.290)	(1665.647)
Distance	-92.99*	-31.06	-165.5**	-94.08***	-45.88**	-115.2**
	(51.809)	(27.398)	(76.747)	(34.109)	(18.389)	(50.507)
Sqrfeet	0.219	0.0615	0.114	0.139	0.0332	0.110
	(0.331)	(0.183)	(0.500)	(0.206)	(0.111)	(0.327)
Doors	630.2*	330.6**	1070.4**	413.5**	190.0**	727.5***
	(331.462)	(148.416)	(452.777)	(208.053)	(85.378)	(279.434)
Windows	217.2**	131.7**	113.4	148.2*	82.60*	91.15
	(108.610)	(61.130)	(134.066)	(81.679)	(42.397)	(98.425)
BldAge	28.23	7.532	11.74	6.067	2.110	9.379
	(32.077)	(16.649)	(42.984)	(20.127)	(11.243)	(27.203)
DeHouse	10609.8***	8778.6***	3774.2	5950.3***	5390.1***	1066.4
	(2960.100)	(2069.810)	(3590.544)	(1759.962)	(1258.408)	(2259.450)
AttHouse	11080.7***	7416.9***	8525.2**	7002.6***	4966.9***	4393.8
	(3271.200)	(2115.329)	(3955.914)	(2224.317)	(1441.865)	(2675.377)
Constant	-48804.1***	-24741.1***	-49851.5***	-28902.7***	-15182.8***	-37195.2***
	(8537.344)	(4861.640)	(12696.778)	(5697.712)	(3255.509)	(9285.540)
Rho						
	0.638***	0.334	0.202	0.425	0.198	0.110
	(0.216)	(0.279)	(0.309)	(0.268)	(0.299)	(0.342)
Lambda						
	0.108	-0.104	-0.161	-0.0284	-0.157	-0.186
	(0.261)	(0.271)	(0.330)	(0.276)	(0.273)	(0.350)
AIC	8129.5	6435.5	3697.4	6979.8	5423.5	3040.2
N	1061	1061	1061	1061	1061	1061

Robust Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Sample Respondents' Characteristics by Property Damage and Insurance Status

Variable	All Respondents	Respondents with Property Damage	Respondents with Insurance	Respondents without Insurance
Average Distance from the Coast (Miles)	14.29	14.10	**14.41**	**13.89**
Flood Zone (%)	13.38	16.31	**21.05**	**13.13**
Flood Insurance (%)	6.97	10.88	**18.80**	**5.56**
Average Years of Residence	17.14	19.71	**21.90**	**18.24**
Concern about hurricane (%)				
No Concern	6.50	6.04	**5.26**	**6.57**
Low Concern	17.53	15.41	**10.53**	**18.69**
Moderate Concern	47.13	42.90	**45.11**	**41.41**
High Concern	28.84	35.65	**39.10**	**33.33**
Average Age of Respondents (Years)	53.18	55.65	**56.53**	**55.06**
Level of education (%)				
Less than high school	1.04	0.30	**0**	**0.51**
High school	10.84	8.76	**6.77**	**10.10**
Some college	27.33	27.79	**31.58**	**25.25**
Bachelor's degree or higher	60.79	63.14	**61.65**	**64.14**
Gender (%)				
Female	58.06	58.31	**55.64**	**60.10**
Male	41.94	41.69	**44.36**	**39.90**
Average Household Size	2.49	2.63	**2.54**	**2.69**
Average Income (in dollars)	\$60,000 to \$74,999	\$60,000 to \$74,999	**\$75,000 to \$84,999**	**\$60,000 to \$74,999**
N	**1061**	**331**	**133**	**198**

Table 6 Logit Regression on Insurance Purchase among Respondents with Property Damage [Dep Variable: Having Insurance Coverage (Yes=1, No=0)]

	(1)	(2)
Distance from the Coast	0.0128	0.0148*
	(0.009)	(0.009)
Flood Zone	0.770**	
	(0.333)	
Flood Insurance		1.559***
		(0.396)
Years of Residence	0.0229**	0.0218**
	(0.009)	(0.009)
Concern about Hurricane	0.245*	0.293**
	(0.144)	(0.147)
Age	-0.00613	-0.00477
	(0.010)	(0.010)
Education	-0.00179	-0.00615
	(0.181)	(0.189)
Gender	-0.154	-0.0849
	(0.241)	(0.247)
Household Size	-0.0884	-0.0934
	(0.102)	(0.106)
Income	0.0545*	0.0552*
	(0.033)	(0.033)
Constant	-1.861*	-2.225*
	(1.130)	(1.151)
AIC	448.4	437.2
N	331	331

Robust Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$