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ORIGINAL PAPER

Hurricane Sandy: Damages, Disruptions and Pathways to Recovery

Sisi Meng[1] · Pallab Mozumder[2]

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Abstract
Critical infrastructure and public utility systems are often severely damaged by natural disasters like hurricanes. Based on a framework of household disaster resilience, this paper focuses on the role of utility disruption on household-level recovery in the context of Hurricane Sandy. Using data collected through a two-stage household survey, it first confirms that the sample selection bias is not present, thus the responses can be estimated sequentially. Second, it quantitatively examines factors contributing to hurricane-induced property damages and household-level recovery. The finding suggests that respondents who suffered from a longer period of utility disruptions (e.g., electricity, water, gas, phone/cell phone, public transportation) are more likely to incur monetary losses and have more difficulty in recovering. Effective preparedness activities (e.g., installing window protections, having an electric generator) can have positive results in reducing adverse shocks. Respondents with past hurricane experiences and higher educational attainments are found to be more resilient compared to others. Finally, the paper discusses the implications of the findings on effective preparation and mitigation strategies for future disasters.

Keywords Household recovery · Utility disruption · Hurricane sandy · Hurricane preparation

Introduction

Critical infrastructure and public utility systems that provide goods and services are often severely damaged by natural disasters, such as hurricanes. The United Nations (2015) Sustainable Development Goals have stressed the urgent need of developing reliable, resilient, and sustainable infrastructure to support economic development and human well-being. The

✉ Sisi Meng
smeng@nd.edu

[1] Keough School of Global Affairs, University of Notre Dame, Notre Dame, IN, USA

[2] Department of Earth and Environment, Department of Economics and Institute of Environment, Florida International University, Miami, FL, USA

recent Sendai Framework for Disaster Risk Reduction (2015) also called for addressing disaster risk in publicly owned, managed, or regulated services and infrastructures, as well as promoting and providing incentives for actions by households, communities, and businesses. When a hurricane strikes, the infrastructure system failure can affect households and communities in many ways, ranging from minor inconveniences (such as power outages of short duration) to more severe disruptions (such as extended loss of utilities and public services for days and weeks, and the long-term shut-down of bridges, roads, and other transportation networks). This paper aims to better understand disaster resilience with a guiding research question: What is the impact of utility disruptions on post-hurricane recovery at the household level?

"Infrastructures support the safety, well-being, and economic vitality of our society" (Guidotti et al. 2016). Disaster literature has emphasized community dependence on the restoration of utility services in the recovery process. Bruneau et al. (2003) indicated that critical lifelines, such as water, power, and critical facilities, are instrumental for overall community functioning and resilience. Liu et al. (2005) highlighted that hurricane-related damages to the electric power system cause significant economic losses, business interruption, and costly restoration efforts. McDaniels et al. (2008) used flow diagrams for presenting the role of decision-making in the overall activities (planning, mitigation, adaptation, and recovery) to foster infrastructure system resilience during extreme events. It is also highly possible that communities suffer from cascading effects of service disruptions, exacerbating response and recovery efforts (Chang et al. 2014). Santella et al. (2009) stated that, to best protect public welfare, the policy must take into account all available information, including the dependencies and interdependencies within and across infrastructures. Overall, rapid restoration following a hazardous event is crucial to the recovery of the affected communities (Han et al. 2009).

Several studies have tried to quantitatively estimate the community impact of utility disruptions caused by natural disasters. Chang et al. (2002) developed an integrated engineering-economic loss estimation model to explore the economic losses resulted from an earthquake. Bruneau et al. (2003) presented a framework that specifies three quantitative measures of community resilience: reduced failure probabilities, reduced consequences from failures, and reduced time to recovery. Alternative approaches to hazard loss estimation included input–output (I-O) modeling and computable general equilibrium (CGE) models. For example, Rose and Liao (2005) studied the impact of water supply disruptions due to an earthquake in the Portland metropolitan area using CGE analysis. Some other studies focused on estimating the effects of utility disruptions on business discontinuity and resilience (Tierney 2007; Sydnor et al. 2017). Their research is vital because recovery also depends on infrastructure and business resilience (Rose and Lim 2002).

A few researchers utilized the contingent valuation methods to elicit households' willingness to pay to avoid power outage (Doane et al. 1988; Carlsson et al. 2011; Ozbafli and Jenkins 2016) or to increase water supply reliability (Howe et al. 1994; Griffin and Mjelde 2000). However, very few theoretical and empirical works have focused on directly estimating the household-level impacts of utility service disruptions due to disasters. Hasan and Foliente (2015) provided a review of the literature related to modeling infrastructure systems performance and the socioeconomic impacts of its failures. Chatterjee and Mozumder (2015) found that disruption of public utility services (e.g., water supply, electricity and telephone) and the suspension of local economic activities (e.g., transportation and local businesses) result in significant losses for households' well-being during Hurricane Wilma. However, due to limited survey data, they used the self-reported impact (from not so serious to very serious) of the hurricane to measure household well-being, without looking into household recovery process. Hurricane impacts are largely due to their exposure to hurricane wind, and those who suffered a similar degree of utility disruptions could experience a very different level of recovery. Chang et al. (2014) described a simulation model of disaster recovery that included the whole community and its interactions between households, businesses, and infrastructure systems. Nonetheless, other than Chang and her coauthor's works, no conceptual framework of the recovery process at the household level can be clearly identified in the literature (Marshall and Schrank 2014).

On the other hand, literature has paid considerable attention to households' socio-economic characteristics, as disasters tend to differentially impact households because of pre-disaster levels of social vulnerability (Cutter et al. 2003). Mitsova et al. (2018) found a positive correlation between power outages and social vulnerability indicators, including minority groups, population with disability, and unemployment rate. A common pattern has shown that low-income households are particularly vulnerable since their initial assets are already lacking, and their abilities to mobilize resources to cope with negative shocks are limited (Morris et al. 2002; Fothergill and Peek 2004; Masozera et al. 2007; Sawada 2007). Age, schooling, and household size are some of the characteristics often examined in the literature. For example, some groups, such as older households or households with larger family sizes, are more likely to be displaced by hurricanes (Morrow 1999; Peacock 2003; Frankenberg et al. 2011). The elderly or children may have mobility constraints or concerns that increase the burden of care and slow recovery (Cutter et al. 2003). Other groups might be educationally disadvantaged, as lower educational attainments constrain the households' ability to understand necessary information that may expedite recovery. Muttarak and Lutz (2014) found that education is consistently more important than income in reducing disaster vulnerability. Educated people adapt more readily as economic circumstances change, using their assets more efficiently, obtaining better credit arrangements, and exploiting new income sources more quickly (Schulz 1975; Glewwe and Hall 1998).

Past hurricane experience may have contributed to the quicker recovery. Research has found that households with disaster-related knowledge and experiences are less impacted in the first place because they are more likely to undertake protective actions or adjustments (Faupel and Styles 1993; Peacock et al. 2005). Relevant knowledge and skills can help them acquire necessary assistance, claim insurances and receive compensation more efficiently. Households with past hurricane experiences are also generally less worried or stressed (Hallstrom and Smith 2005). Becker et al. (2017) examined various types of disaster experience and summarized seven predominant influences on preparedness, including promoting thinking and talking, promoting community interaction, raising awareness and knowledge, understanding the consequence, developing beliefs, developing personal skills, and influencing emotions.

Studies have also shown that preparation activities (e.g., self-protective actions and obtaining the needed resources) can be important determinants for an effective response and recovery (Tierney et al. 2001). For example, mitigation measures targeted to reduce wind-related damages (e.g., shutters, hurricane resistant windows and doors) and alternative resources for dealing with emergencies (e.g., electric generator and hurricane supplies) can be effective (Chatterjee and Mozumder 2015). Purchasing insurance is often an essential element in managing disaster risks and promoting recovery (Wouter Botzen 2013). Households who lost their homes, possessions, and jobs can get by from their insurance coverage to replace their property and wage losses. Evidence has suggested that the lack of adequate insurance coverage is mainly due to the high premium and the lack of knowledge. This further supports the contention that wealthy and more educated households are more likely to speed up recovery through adequate coverage (Mileti 1999). Of course, one should not ignore the "moral hazard" issue associated with insurance coverage. Fronstin and Holtmann (1994) pointed out that insurance coverage may reduce individuals' incentive to protect their property during a hurricane.

On the 29th of October 2012, Hurricane Sandy made landfall in the United States as a Category 1 hurricane, striking near Atlantic City, New Jersey. The storm caused widespread and long-lasting disruptions to infrastructure systems and utility services in the northeastern region, especially in the New York and New Jersey areas, providing an opportunity to study the impact of utility disruptions. In this paper, we adapted the previous disaster resilience framework that focused only on assessing the loss of infrastructure resilience. In order to better measure household well-being, we introduced an extended household resilience framework that not only examines the loss of household resilience due to utility disruptions, but also identifies different responses and strategies undertaken by households and their socio-economic characteristics that influence the recovery process. More specifically, we attempt to answer three questions: How do utility disruptions affect households' recovery? To what extent do these disruptions affect households? What types of households are more resilient (that is, faster in recovering regarding health, finances, and property) from Hurricane Sandy? To address these questions, we have conducted a household survey eight months after Hurricane Sandy. Respondents were first asked to state their monetary damages caused by Sandy, and those who reported a positive amount of damage were asked to rate their recovery levels at the second stage. We also empirically test the role of preparedness activities and socio-economic characteristics in the recovery process. Last, to control differential hurricane exposures, households' spatial location was utilized to construct the control variable wind speed.

Research Framework

We define household disaster resilience as their ability to recover from the adverse shocks of a disaster and incorporate the benefit of preparedness activities and diverse socio-economic characteristics into the framework. Suppose that a household's well-being (W) is assessed by getting the greatest value possible from the expenditure of goods Z (E_Z) derived from the income (I), and the household-related characteristic vector (H). The household's objective is therefore to maximize:

$$W = W(E_Z, I, H) \tag{1}$$

subject to an income constraint:

$$\sum E_Z Z \leq I \tag{2}$$

The initial level of household's well-being can be written as:

$$W_0 = W(E_{Z0}, I_0, H_0) \tag{3}$$

Now, each household in Sandy-affected areas faced a decision to whether to engage in preparation actions before the landfall of the hurricane. Once the decision was made and Sandy made landfall, some households could experience higher monetary damages due to the wind-induced utility disruptions. Others may suffer from less utility disruptions that cause less damages to the households. The decision framework and the associated outcomes are presented in Fig. 1.

Starting from the top of the diagram, an effective preparation measure is expected to reduce hurricane-induced damages and alleviate the loss of household well-being. The net benefit of such a decision is measured by the benefit of preparation minus the associated cost ($B_P - C_P$). If the household was prepared and incurred damages, the outcome becomes $B_P - C_P - C_D$, where C_D presents the cost of the disruptions. Without preparation, households could yield either an outcome of 0 or an outcome of $-aC_D$. Note that the cost of disruptions tends to be worse for unprepared households, captured by a weight a, where $a > 1$. Figure 2 illustrates the above setup to compare the best outcomes with the net benefit of preparedness being positive ($B_P > C_P$) or negative ($B_P < C_P$).

Case 1 ($B_\mathbf{P} > C_\mathbf{P}$)

We begin with the case where the benefit of preparedness is greater than the cost. If there was no disruption (see the "No Disruption" branches in Fig. 1), $B_P - C_P$> 0, households should take the preparedness actions to achieve a better outcome (e.g. households who install wind-resistant doors and windows may qualify for home insurance discounts irrespective of hurricane events).

We are more interested in situations where households experienced monetary damages from hurricane-induced utility disruptions ($C_D \neq 0$). Figure 2a illustrates the temporal dynamics of both prepared and unprepared households to the consequences of a hurricane (from t_0 to t_1), and the recovery from the effects (from t_1 to t_2). As shown, households who were prepared for the storm could result in a higher level of well-being, indicated as $W(t)$. They suffer from a disruption of D_1 and have access to a higher path, $W_1(t)$, during the recovery period. Unprepared households will suffer a more severe disruption, D_2, and recover through the lower path at $W_2(t)$.

We assume that the cost or damage of D_1 equals to C_D and the cost of D_2 equals to aC_D. W_0 is the initial level of household well-being from Eq. (1), and $W(t)$ is the level of household well-being at any time t. Also note that t_1 can be found at any point between t_0 and t_2, because the starting point of the recovery process is not uniform among households. Next, we compare

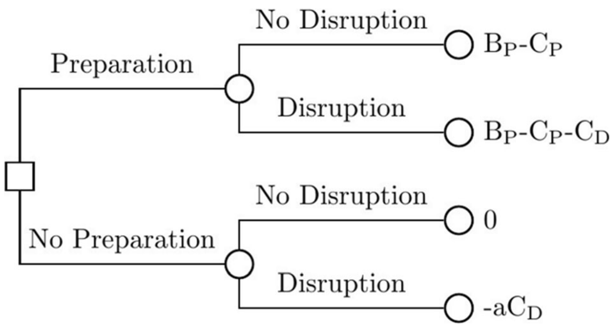

Fig. 1 The decision framework. Notes: This figure shows the decision framework of preparedness measures undertaken by households and the associated outcomes. The net benefit of hurricane preparedness is measured by the benefit of preparation minus the cost of preparation ($B_P - C_P$). If the household is prepared but incurred damages, the outcome becomes $B_P - C_P - C_D$, where C_D presents the cost of the disruptions. Note that the cost of disruptions tends to be worse for unprepared households, captured by a weight a, where a >1

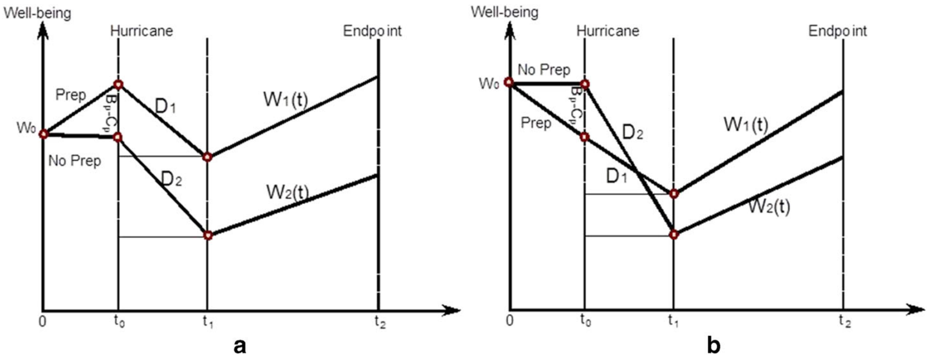

Fig. 2 Dynamic framework of household resilience. Notes: This figure illustrates the temporal dynamics of household responses to the consequences of hurricane and the recovery. Figure 2**a** is the case when the benefit of preparedness is greater than the cost. Figure 2**b** is the case when the benefit of preparedness is lower than the cost. Household resilience R_i can be measured by integrating the areas under the level of household well-being $W_i(t)$

the household resilience (R) by integrating the areas under $W_1(t)$ and $W_2(t)$, to compare the outcomes presented in Fig. 2a.[1]

The resilience of prepared households (R_1) is measured as:

$$W_1(t) = W_0 + (B_P - C_P) - C_D e^{-b_1 t} \tag{4}$$

$$R_1 = \frac{\int_{t_1}^{t_2} [W_1(t)]dt}{(t_2 - t_1)} = \frac{\int_{t_1}^{t_2} \left[W_0 + (B_P - C_P) - C_D e^{-b_1 t}\right] dt}{(t_2 - t_1)} \tag{5}$$

Similarly, the resilience of unprepared households (R_2) is measured as:

$$W_2(t) = W_0 - aC_D e^{-b_2 t} \tag{6}$$

$$R_2 = \frac{\int_{t_1}^{t_2} [W_2(t)]dt}{(t_2 - t_1)} = \frac{\int_{t_1}^{t_2} \left[W_0 - aC_D e^{-b_2 t}\right] dt}{(t_2 - t_1)} \tag{7}$$

b_1 is the slope of the $W_1(t)$ path and b_2 is the slope of the $W_2(t)$ path. We assume $b_1 \geq b_2$, because households who take preparation actions are expected to be associated with higher socio-economic status (Elliott and Pais 2006), which further contributes to a higher speed of recovery process.

$$\begin{aligned} \text{Now, } W_1(t) - W_2(t) \quad &= \left[W_0 + (B_P - C_P) - C_D e^{-b_1 t}\right] - \left[W_0 - aC_D e^{-b_2 t}\right] \\ &= (B_P - C_P) - C_D e^{-b_1 t} + aC_D e^{-b_2 t} \\ &\geq (B_P - C_P) - C_D e^{-b_1 t} + aC_D e^{-b_1 t} \\ &= (B_P - C_P) + (a-1)C_D e^{-b_1 t} > 0 \ (a > 1) \end{aligned} \tag{8}$$

[1] The idea of using the area under $W(t)$ to present household resilience is adapted from Zobel (2011) and inspired by other later works with his co-authors (Zobel and Khansa 2014; Davis et al. 2019), which utilized the area of triangle to indicate the loss of disaster resilience.

Therefore, $W_1(t) > W_2(t)$ and $R_1 > R_2$, implying that prepared households have access to a higher level of well-being compared to unprepared households. Preparedness activities and socio-economic characteristics can contribute to a higher level of household resilience.

Case 2 ($B_P < C_P$)

Next, we study the case when the benefit of preparedness is less than the cost. If there was no hurricane-induced disruption, $B_P - C_P < 0$, the net benefit of preparedness becomes negative. Households may not take self-protective actions at such a high cost.

We next examine the situation where households experienced damages from utility disruptions (see Fig. 2b). Would the households still benefit from hurricane preparation? According to the "Disruption" branches in Fig. 1, prepared households could yield a better outcome if:

$$B_P - C_P - C_D \geq -aC_D \tag{9}$$

Or

$$C_P - B_P \leq (a-1)C_D \ (a > 1) \tag{10}$$

$$\begin{aligned} \text{Under this condition, } W_1(t) - W_2(t) &= \left[W_0 + (B_P - C_P) - C_D e^{-b_1 t}\right] - \left[W_0 - aC_D e^{-b_2 t}\right] \\ &= (B_P - C_P) - C_D e^{-b_1 t} + aC_D e^{-b_2 t} \\ &\geq (B_P - C_P) - C_D e^{-b_1 t} + aC_D e^{-b_1 t} (\text{Assume } b_1 \geq b_2) \\ &= (B_P - C_P) + (a-1)C_D e^{-b_1 t} \\ &\geq (B_P - C_P) + (C_P - B_P)e^{-b_1 t} \\ &= (C_P - B_P)\left(e^{-b_1 t} - 1\right) > 0 \end{aligned} \tag{11}$$

Therefore, $W_1(t) > W_2(t)$ and $R_1 > R_2$, under the condition expressed in (10).

Hurricane preparedness can be beneficial to households when its net cost is less than the difference in damages caused by wind-induced utility disruptions. This is especially important for low-income households. Hazard adjustment, such as shutters and other retrofitting processes, often requires a significant amount of investment. The level of preparedness has been shown to be inadequate among low-income population (Dominianni et al. 2018; Ge et al. 2011). Since many households have limited financial resources to allocate in a disastrous event, policies that lower the costs of their preparedness activities (e.g., insurance premium discounts) can be very useful.

To sum up, the area of household resilience R is determined by the effective preparation at low cost ($B_P - C_P$), the extent of damages caused by hurricane-induced disruptions (C_D), and the ability to quickly recover (b). Particularly, the speed of the recovery (b) is related to households' socio-economic characteristics. Based on this household resilience framework, we will empirically test these determinants with the following model:

$$R_i = f(D, P, H) \tag{12}$$

where R is resilience measured by recovery of household i. The variables included in vector D consist of five types of utility disruptions experienced by households. The variables included in vector P and vector H consist of preparedness activities and household socio-economic characteristics, respectively.

Data and Sample Characteristics

The data comes from a household survey designed by researchers at the Social Science Laboratory of the International Hurricane Research Center (IHRC) at Florida International University (FIU). GfK (formerly known as Knowledge Networks), a reputed organization that routinely implements a variety of public opinion surveys, conducted the survey through the internet on behalf of IHRC over a period of two weeks (July 7 – 22, 2013). The targeted population consisted of eligible adults (ages 18 and older) who resided in Hurricane Sandy's most affected areas in ten states.[2] The respondents were randomly selected through probability-based sampling from the KnowledgePanel by GfK, a probability-based web panel designed to be representative of the United States. Among the 3,276 adults in the full sample, 2,028 completed the survey (a completion rate of 61.93%) and 1,212 were identified as qualified completion (a qualification rate of 59.76%).

Respondents were asked to participate in the survey in two stages (See Fig. 3). At the first stage, they were asked to report any monetary loss caused by Sandy. Five types of damages were reported: exterior home damage, interior home damage (e.g., walls, ceilings, floors, etc.), damage to furniture, damage to internal contents (e.g., computers, books, jewelry, tools, etc.), and damage to automobiles. At the second stage, only respondents who reported a positive amount of any type of above damages were asked to rate how well they have recovered from the effects of Hurricane Sandy (on a scale of 0 to 10, while 10 indicated a level of "fully recovered" and 0 a level of "not recovered at all"). Because this self-rated level is usually seen as subjective from one individual to another, concerns may arise. For instance, an individual who believed that he or she was almost recovered might report a number of 9, while the other who thought the same way may only report a number of 6. To mitigate this possible subjective bias, we have reclassified the recovery levels into three categories: (1) not well recovered (original rating from 0 to 5); (2) almost recovered (original rating from 6 to 9); (3) fully recovered (original rating of 10).[3] Also, we considered households who were fully recovered at the time of the survey as "resilient households", and households who were not well recovered are "fragile households" and those who were almost recovered stand somewhere in between.

Due to missing information, we used a full sample of 1,042 respondents in the first stage. Map 1 in Fig. 4 presents the number and the location of surveyed respondents by states.[4] As we can see, the majority of them living in the northeastern region and along the east coast were affected by Sandy, with a large proportion from New Jersey (36.56%) and New York (28.41%). This is consistent with the fact that Sandy turned into a huge storm with intense winds when it made landfall over New Jersey. As time progressed, Sandy weakened as it moved inland over Pennsylvania to the northeastern states. Among all the respondents, 334 have reported their damages (32.05%, indicated by red circles) caused by Hurricane Sandy and were asked to participate in the second stage. 150 of them completed the survey (completion rate of 45.51%). According to Map 2 in Fig. 4, 121 out of 150 respondents (80.67%) are from New York or New Jersey. This high proportion further indicates that these two states were truly the "hot spot" of this event. Even though households from the rest of the states were

[2] The states include New Jersey (NJ), New York (NY), Connecticut (CT), Maryland (MD), Massachusetts (MA), Virginia (VA), Delaware (DE), Pennsylvania (PA), Rhode Island (RI), and West Virginia (WV).

[3] No significant differences in the estimation results were found when using the original levels instead of the reclassified three categories. Therefore, we used the three-category setting for simplicity in the analysis.

[4] Figure 4 is prepared by using ArcMap 10.2 software. The location of each respondent is Geo-coded based on the longitude and latitude. Coordinates are in GCS North American 1983.

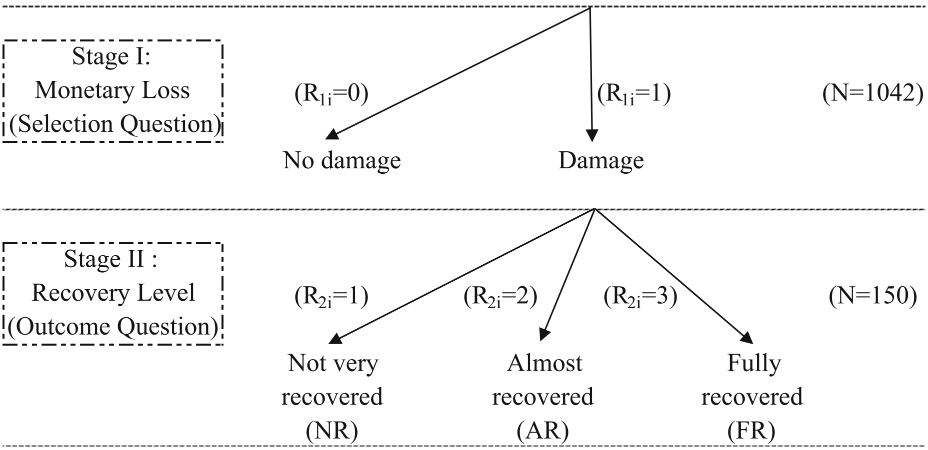

Fig. 3 Survey questions on loss and recovery from hurricane Sandy (2012). Notes: The survey was conducted eight months after Hurricane Sandy (2012). Households were first asked to report monetary losses, and those who reported a positive amount of loss are then asked to rate their current recovery levels

affected as well, most of them did not suffer in terms of monetary loss. In addition, the recovery level rated by each respondent can be located in Map 2. Approximately half of them (45.33%) believed that they "fully recovered" from Hurricane Sandy after eight months. About 37.33% percent stated that they "almost recovered" and 17.33% reported the status "not well recovered".

We utilized three sets of independent variables based on our household resilience framework in Eq. (12). The first set of variables included five essential utility systems or services: electricity, water, gas, phone/cell phone, and public transportation. Respondents were asked to estimate how many days they experienced disruptions for each of these services. Figure 5 gives a general picture of the percentage and duration of each utility disruption reported by respondents from the full sample.[5] Among those who lost electricity, the majority reported a disruption for less than a week (of which, 35.73% reported being without electricity for less than three days and 37.70% for four to seven days). Around 23.82% of respondents lost electricity for more than a week but less than two weeks (8 – 14 days). A smaller proportion of respondents had to put up with a longer period without electricity: 2.49% for more than two weeks but less than one month (15 – 30 days) and 0.26% for more than one month. Similar patterns were found for disruptions in the other four utility services, indicating that most households were able to resume normal activities within one week, at most two weeks.

The second set of variables included self-protective actions and alternative resources undertaken by households for dealing with hurricane impacts. The first variable used is insurance coverage, and respondents were asked if they had an insurance policy that paid for damages to their homes from a storm or hurricane. The second and third variables utilized were window protection and generator. Respondents were asked if they had any kind of protection (such as storm shutters, security film, or plywood) to protect the windows and if they owned an electric generator during Hurricane Sandy. More than half of the respondents

[5] We did not present the disruption rate of each utility service in Fig. 5. In fact, 73.32% of respondents have reported electricity disruption, 12.76% have reported water disruption, 15.26% have reported gas disruption, and 46.93% and 33.97% have reported phone/cell phone and public transportation disruption, respectively.

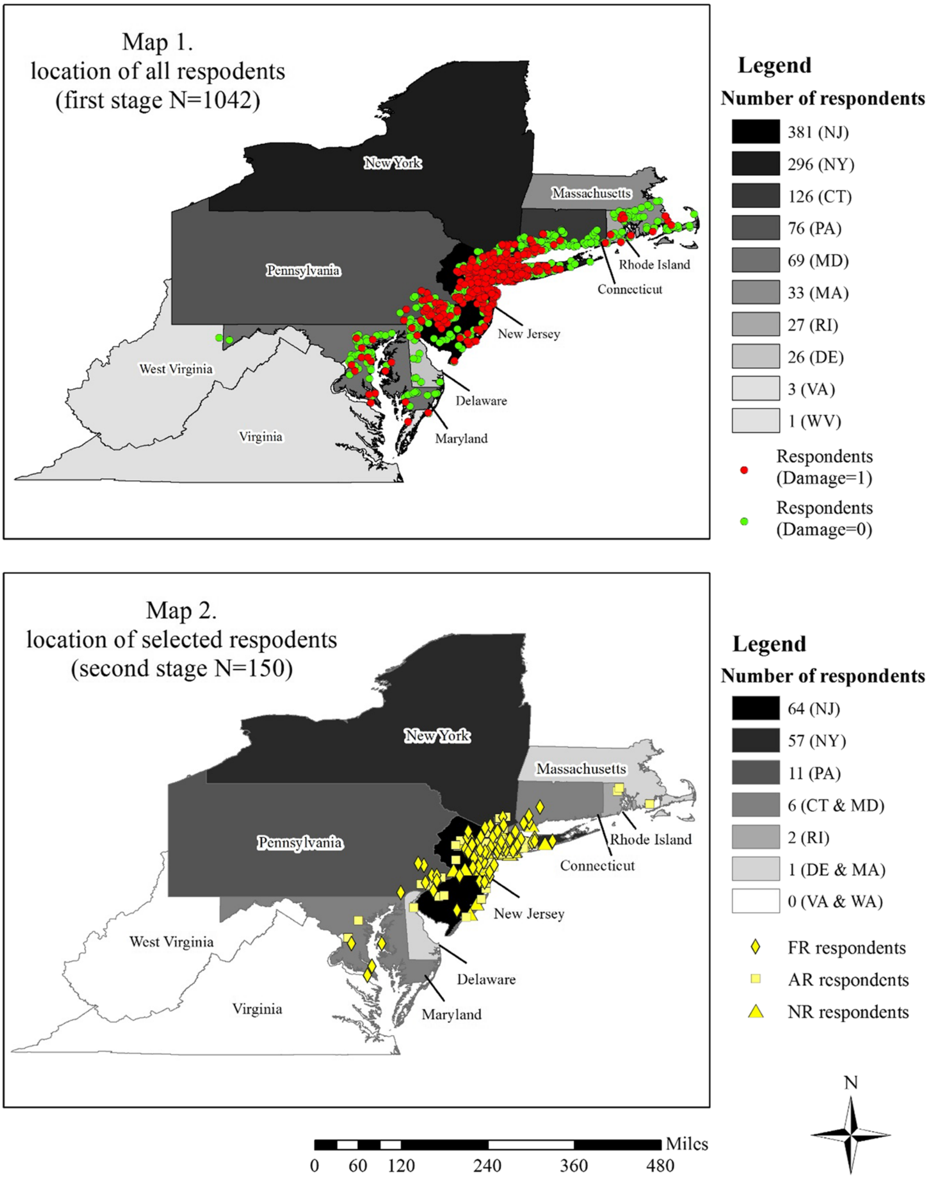

Fig. 4 Location of surveyed respondents by States

(61%) had an insurance policy, and 24% owned an electric generator. However, only 7% of them installed any kind of window protection in preparation for Sandy.

The third set of variables consisted of various household socio-economic characteristics, such as age, education, income, family size, and years of residence. We also included whether households have past hurricane experiences, whether they locate in a flood zone, and state-level dummy in the analysis. The respondents' average age was 53 years old, and the average household size was 2.49. The average year of residence was 17 – 18 years. About 12.57% of the respondents had a high school diploma or less, and 59.98% had a Bachelor's degree or

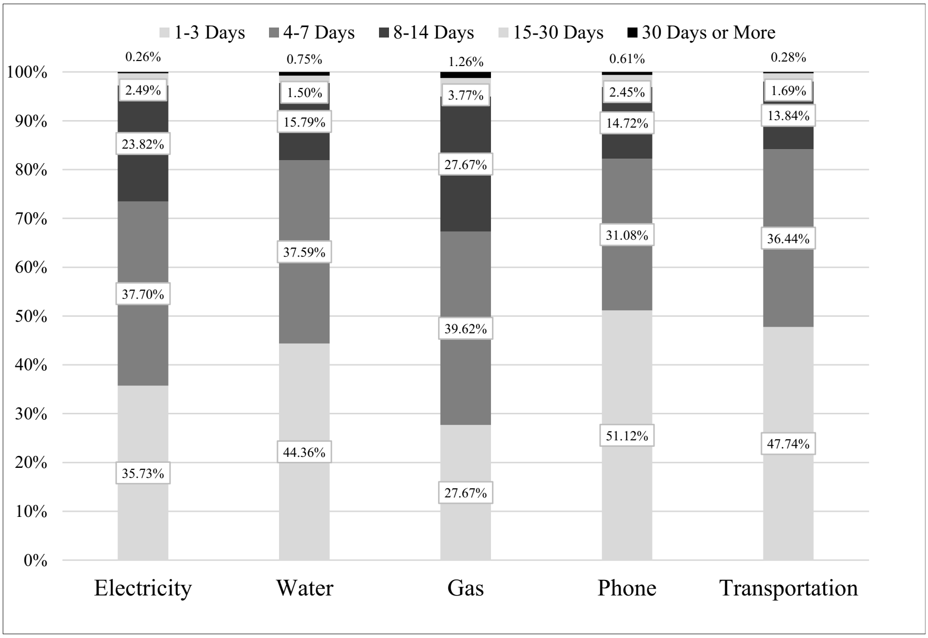

Fig. 5 Statistics on utility disruptions. Notes: Respondents were asked to report how many days they experienced disruptions on five different types of utility services. This figure shows the percentages and duration of the disruptions reported

higher. The average annual income level ranged from $60,000 to $75,000. Sixty-eight percent of the respondents had hurricane experience as they indicated that they were living in an area impacted by Hurricane Irene in 2011.[6] Thirteen percent of them indicated that they live in a flood zone.

Apart from utilizing the survey responses, we have also measured the characteristics of Hurricane Sandy by using HAZUS-MH (Hazard U.S. – Multi-Hazard) Hurricane Model to control for the intensity of the hurricane.[7] The strength of hurricanes is usually measured by wind speeds.[8] The model uses wind engineering principles and generates validated wind speeds by comparing simulated and observed wind speeds. We have first provided the necessary inputs to build the Hurricane Sandy scenario in the model. The inputs are taken from National Hurricane Center's North Atlantic hurricane database (HURDAT), which consists of six-hourly positions (latitude, longitude, translation speed, and time) and corresponding intensity estimates (radius to hurricane winds, maximum wind speed, and central pressure) of Sandy. The model is then implemented to generate Sandy's track and the maximum sustained wind speeds at each census tract for the ten states in our study region.

[6] Hurricane Irene (2011) marked one of the most damaging hurricanes to make landfall prior to Hurricane Sandy in the New York and New Jersey areas.

[7] HAZUS is a geographic information system (GIS) -based natural hazard developed and freely distributed by the Federal Emergency Management Agency (FEMA). For technical details, see: http://www.fema.gov/media-library-data/20130726-1820-25045-8522/hzmh2_1_hr_um.pdf

[8] Wind speed is likely to positively correlate with utility disruption, and omitting it will potentially overestimate the impact of utility disruption. We acknowledge that using Census tract provides only a rough estimation of the wind speed, and errors may be present from the HAZUS estimation. However, we believe the wind speed from HAZUS estimation can be used as a good control variable to enrich the survey data.

Finally, the estimation of wind speed experienced for the respondents was obtained by spatially joining the census-track level wind speed into their geocoded locations. Although respondents in the same census tract have the same wind speed, we are still able to capture enough variation to account for the wind impact. The description of all variables used is presented in Table 1. The detailed statistics of each variable on the full sample (from the first stage) and the subsample (from the second stage) can be found in Table 2.

Estimation Results

Due to the fact that our analysis at the second stage is restricted to households who reported monetary damages, the sample selection bias may be present (Heckman 1979). More

Table 1 Description of variables

	Description
Explained variables	
Damage	If respondents had any monetary lost due to hurricane Sandy (1=yes, 0=no)
Recovery	Recovery level from the effects of Hurricane Sandy (1=Not recovered; 2=Almost recovered; 3=Fully recovered)
Explanatory variables	
Wind	Maximum sustained wind speed (miles per hour)
Electricity	Days respondents experienced disruptions in electricity
Water	Days respondents experienced disruptions in water
Gas	Days respondents experienced disruptions in gas
Phone	Days respondents experienced disruptions in phone/cell phone
Transportation	Days respondents experienced disruptions in transportation
Insurance	If respondents had an insurance policy that paid for damages from a hurricane (1=yes, 0=no)
Protection	If respondents had any kind of window protection such as storm shutters, security film, or plywood to protect the windows (1=yes, 0=no)
Generator	If respondents owned an electric generator (1=yes, 0=no)
Irene	If respondents lived in an area impacted by Hurricane Irene (1=yes, 0=no)
Age	Age of households in years
Education	Highest level of education (1=Less than high school 2=High school; 3=Some college; 4=Bachelor's degree or higher)
Income	Level of household income[a]
Size	Number of people lived in the household
Years	Number of years lived at the address
Floodzone	If the respondent lives in a flood zone (1=Yes, 0=Otherwise)
RI	If the respondent lives in the state of Rhode Island (1=Yes, 0=Otherwise)
CT	If the respondent lives in the state of Connecticut (1=Yes, 0=Otherwise)
NY	If the respondent lives in the state of New York (1=Yes, 0=Otherwise)
NJ	If the respondent lives in the state of New Jersey (1=Yes, 0=Otherwise)
PA	If the respondent lives in the state of Pennsylvania (1=Yes, 0=Otherwise)
DE	If the respondent lives in the state of Delaware (1=Yes, 0=Otherwise)
MD	If the respondent lives in the state of Maryland (1=Yes, 0=Otherwise)
MA	If the respondent lives in the state of Massachusetts (1=Yes, 0=Otherwise)
Other	If the respondent lives in the state of Virginia or West Virginia (1=Yes, 0=Otherwise)

a: The income levels are: 1 = Less than \$5,000; 2 = \$5,000 to \$7,499; 3 = \$7,500 to \$9,999; 4 = \$10,000 to \$12,499; 5 = \$12,500 to \$14,999; 6 = \$15,000 to \$19,999; 7 = \$20,000 to \$24,999; 8 = \$25,000 to \$29,999; 9 = \$30,000 to \$39,999; 10 = \$35,000 to \$39,999; 11 = \$40,000 to \$49,999; 12 = \$50,000 to \$59,999; 13 = \$60,000 to \$74,999; 14 = \$75,000 to \$84,999; 15 = \$85,000 to \$99,999; 16 = \$100,000 to \$124,999; 17 = \$125,000 to \$149,999; 18 = \$150,000 to \$174,999; 19 = \$175,000 or more

Table 2 Descriptive statistics of each variable in the sample

Group	Full Sample (N = 1042) (First Stage)				Subsample (N = 150) (Second Stage)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Damage	0.32	0.47	0	1	1	0	1	1
Recovery	2.28	0.74	1	3	2.28	0.74	1	3
Wind	71.34	7.64	50	95	73.99	7.13	51	92
Electricity	4.28	5.08	0	70	7.85	8.62	0	70
Water	0.68	2.78	0	60	1.77	6.02	0	60
Gas	1.10	3.89	0	60	2.76	8.14	0	60
Phone	2.33	4.40	0	60	4.48	7.01	0	60
Transportation	1.73	3.99	0	50	2.68	5.72	0	50
Insurance	0.61	0.49	0	1	0.82	0.39	0	1
Protection	0.07	0.25	0	1	0.22	0.42	0	1
Generator	0.24	0.43	0	1	0.33	0.47	0	1
Irene	0.68	0.47	0	1	0.69	0.47	0	1
Age	53.39	15.17	18	91	56.29	13.80	19	85
Education	3.46	0.74	1	4	3.50	0.65	2	4
Income	13.40	4.04	1	19	14.20	3.61	3	19
Size	2.49	1.27	1	10	2.57	1.34	1	10
Years	17.15	14.02	0	68	21.11	14.75	0	68
Floodzone	0.13	0.33	0	1	0.20	0.40	0	1
RI	0.02	0.16	0	1	0.01	0.12	0	1
CT	0.12	0.33	0	1	0.04	0.20	0	1
NY	0.29	0.45	0	1	0.39	0.49	0	1
NJ	0.37	0.48	0	1	0.43	0.50	0	1
PA	0.07	0.26	0	1	0.07	0.26	0	1
DE	0.02	0.16	0	1	0.01	0.08	0	1
MD	0.07	0.25	0	1	0.04	0.20	0	1
MA	0.03	0.18	0	1	0.01	0.08	0	1
Other	0.00	0.06	0	1	0.00	0.00	0	0

specifically, we compare the recovery performance of households who experienced longer disruptions to those who experienced shorter disruptions. The group of households who suffered higher damages is included in our sample because they have longer disruption, and they will be representative of the group with longer disruptions. However, the subset of households with zero damages will not be representative of the group of households with short disruptions. Some households who experienced longer disruptions may still report zero damages due to their preventative actions. Ultimately, households with longer disruption may have a higher recovery level with zero damages. In that case we may overestimate the effects of utility disruptions and neglect the benefits of hurricane preparation.

For this reason, we first employed a technique that accounts for the sample selection bias and accommodate ordinality of our dependent variables (Miranda and Rabe-Hesketh 2006). The ordered logit regressions are estimated by using maximum likelihood methods, and Table 3 presents the estimation results. The column (1) and (2) report the estimation results with sample selection method, by using the joint maximum likelihood estimation of household damage and recovery level.[9] The cross-equation correlation ρ of estimated errors of the

[9] We use a generalized linear latent and mixed model (GLLAMM) with the ssm command in STATA to estimate the ordered logit model with sample selection.

Table 3 Estimation results for household damage and recovery level

	Sample Selection Model		Full Model (Sequential)		Utility Dis Model	Prep. Model	Socio-econ Model
	(1)Damage	(2)Recovery	(3)Damage	(4)Recovery	(5)Recovery	(6)Recovery	(7)Recovery
Wind	0.0301***	0.00704	0.0454***	0.00241			
	(0.011)	(0.026)	(0.012)	(0.044)			
Electricity	0.0593***	-0.0275	0.0909***	-0.0630*	-0.0468*		
	(0.013)	(0.019)	(0.021)	(0.036)	(0.026)		
Water	0.0508**	-0.0728**	0.0566*	-0.140**	-0.153***		
	(0.021)	(0.034)	(0.034)	(0.055)	(0.057)		
Gas	0.0312**	-0.0474***	0.0552**	-0.0897***	-0.0756***		
	(0.015)	(0.014)	(0.025)	(0.025)	(0.025)		
Phone	0.00866	-0.0497*	0.0177	-0.0904*	-0.0691*		
	(0.014)	(0.029)	(0.022)	(0.048)	(0.041)		
Transportation	0.0340***	-0.0146	0.0577***	-0.0333	-0.0309		
	(0.012)	(0.025)	(0.019)	(0.044)	(0.032)		
Insurance	0.311***	0.109	0.518***	0.102		1.041**	
	(0.096)	(0.330)	(0.162)	(0.581)		(0.507)	
Protection	0.635***	1.039***	1.001***	1.655***		1.262***	
	(0.173)	(0.325)	(0.278)	(0.577)		(0.427)	
Generator	0.153	0.455**	0.242	0.742*		0.512	
	(0.106)	(0.219)	(0.176)	(0.395)		(0.339)	
Irene	0.0361	0.532**	-0.0217	0.917*			0.927**
	(0.095)	(0.264)	(0.161)	(0.471)			(0.375)
Age	0.00849**	0.00418	0.0128**	0.00512			-0.000398
	(0.004)	(0.010)	(0.006)	(0.017)			(0.015)
Education	0.117*	0.420**	0.197*	0.694**			0.487*
	(0.066)	(0.172)	(0.112)	(0.303)			(0.260)
Income	0.00230	0.000814	0.000808	0.0000182			-0.0242
	(0.012)	(0.027)	(0.021)	(0.047)			(0.046)
Size	0.104***	0.0569	0.176***	0.0725			-0.0250
	(0.040)	(0.099)	(0.067)	(0.173)			(0.158)
Years	0.00896**	-0.00891	0.0142**	-0.0185			0.00169
	(0.004)	(0.008)	(0.006)	(0.014)			(0.011)
Floodzone	-0.0963	0.00267	-0.018	0.0446			-1.327***

Table 3 (continued)

	Sample Selection Model		Full Model (Sequential)		Utility Dis Model	Prep. Model	Socio-econ Model
	(1)Damage	(2)Recovery	(3)Damage	(4)Recovery	(5)Recovery	(6)Recovery	(7)Recovery
	(0.142)	(0.353)	(0.241)	(0.621)			(0.415)
MD	1.001***	0.320	1.711***	0.335			
	(0.263)	(0.739)	(0.473)	(1.313)			
RI	1.033***	-0.237	1.771***	-0.626			
	(0.332)	(0.707)	(0.583)	(1.264)			
NY	0.594***	0.194	1.063***	0.226			
	(0.200)	(0.643)	(0.363)	(1.169)			
NJ	0.576***	0.164	1.023***	0.171			
	(0.206)	(0.684)	(0.373)	(1.257)			
PA	0.645***	0.358	1.152***	0.522			
	(0.236)	(0.714)	(0.419)	(1.309)			
DE	0.447		0.814				
	(0.334)		(0.596)				
MA	0.655*		1.106*				
	(0.350)		(0.660)				
Other	1.736***		2.956***				
	(0.672)		(1.113)				
Cut1_Cons	-5.226***	1.469	-8.893***	0.609	-3.060***	-0.404	-0.101
	(0.869)	(2.413)	(1.502)	(3.643)	(0.386)	(0.478)	(1.577)
Cut2_Cons		2.998		3.291**	-0.757***	1.530***	1.871*
		(2.402)		(3.644)	(0.266)	(0.520)	(1.556)
rho		0.269					
		(0.293)					
pseudo R^2			0.167	0.252	0.153	0.065	0.0708
Loglikelihood		-659.8	-544.4	-115.6	-130.9	-144.4	-143.6
LR (χ2) Test		229.0	166.12	49.75	31.96	15.01	24.85
N		1042	1042	150	150	150	150

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

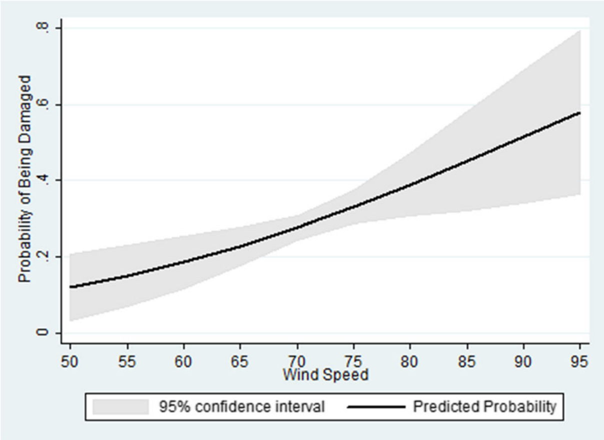

Fig. 6 Predicted probability of damage by wind speed. Notes: The figure presents the predicted probability of reporting positive damages by households exposed to different wind speed levels, and the 95% confidence intervals around the predictions. The probability is ranged from 0.14 when wind speed is 50 miles per hour to 0.55 when wind speed is 95 miles per hour

selection variable (damage) and the outcome variable (recovery) is used to test for sample selection bias. As a result, the likelihood ratio test for null hypothesis of uncorrelated error (ρ = 0) cannot be rejected (p = 0.56), suggesting that the samples in the second stage are randomly selected with no selection bias. Therefore, we can obtain consistent estimators by estimating the two regression equations sequentially at both stages.[10] Column (3) reports the logit regression on hurricane-induced damages for all households from the first stage. The rest of the columns present four models predicting household-level recovery using ordered logit regressions, with selected households from the second stage.

As expected, wind speed has a significant and strong positive impact on damage (see column 3). The predicted probabilities of reporting positive damage by respondents at different wind speeds are presented in Fig. 6. The positive effect is evident by the increasingly larger probabilities on damage as wind speed increases (from 0.12 when wind speed is 50 miles per hour to 0.58 when wind speed is 95 miles per hour). The 95% confidence intervals around the predictions are also added, which are smaller near the center of the data where wind speed is around 75 miles per hour and increases as we move to lower or higher wind speeds.

We then examine the effects of utility disruptions on households' activities. According to Table 3, disruptions in electricity, water, gas, and public transportation had significant impacts during Hurricane Sandy. A longer duration of disruptions of these utilities increases the possibility of incurring damages at the first stage. Also, electricity outage reveals a stronger impact on damage than disruptions in other utilities, indicated by a larger coefficient. In terms of recovery, disruptions in electricity, water, gas and phone are found to be statistically significant with expected negative signs. Households who experienced longer days of these disruptions are less likely to have a higher level of resilience. As shown in column (5) in Table 3, the utility disruption model accounts for 15.3% of the variance, explaining the differential recovery outcomes very well. It is also useful to interpret the results by computing the marginal effects on each level of recovery (see Table 4). Water supply is identified as the

[10] Note that there are no substantial differences on the estimation results between ordered logit regression with and without sample selection method.

Table 4 Marginal effects for estimated household damages and recovery levels[b]

	Damage	NR (Rec = 1)	AR (Rec = 2)	FR (Rec = 3)
Wind	0.00945***	-0.000229	-0.000332	0.000561
Electricity	0.0189***	0.00596*	0.00865	-0.0146*
Water	0.0118*	0.0132**	0.0192**	-0.0324**
Gas	0.0115**	0.00849***	0.0123***	-0.0208***
Phone	0.00368	0.00856*	0.0124*	-0.0210*
Transportation	0.0120***	0.00315	0.00457	-0.00772
Insurance (d)	0.105***	-0.00989	-0.0135	0.0234
Protection (d)	0.235***	-0.114***	-0.277**	0.391***
Generator (d)	0.0515	-0.0641*	-0.112*	0.176*
Irene (d)	-0.00452	-0.100	-0.0994**	0.200**
Age	0.00267**	-0.000485	-0.000703	0.00119
Education	0.0411*	-0.0657**	-0.0954**	0.161**
Income	0.000168	-0.00000172	-0.00000250	0.00000422
Size	0.0367***	-0.00687	-0.00997	0.0168
Years	0.00295**	0.00176	0.00255	-0.00431
Floodzone	-0.00368	-0.00418	-0.00621	0.0104
MD	0.402***	-0.0281	-0.0524	0.0805
RI	0.416***	0.0750	0.0556	-0.131
NY	0.234***	-0.0210	-0.0317	0.0527
NJ	0.220***	-0.0161	-0.0238	0.0399
PA	0.270***	-0.0415	-0.0849	0.126
DE	0.189			
MA	0.261			
Other	0.598***			
	1042	150	150	150

b: NR is the level of "Not Recovered", AR is the level of "Almost Recovered" and FR is the level of "Fully Recovered". (d) is for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

most influencing utility service at the recovery stage, indicated by the larger marginal effect. Without a doubt, water is an essential element of survival. In the aftermath of a hurricane, it is critical to have sufficient clean water for household consumption, maintaining basic hygiene, and resuming normal activities. According to Table 4, the marginal effect of water is 0.0132 in the NR column, indicating that each additional day of water disruption increases the probability of being "not well recovered" by 1.32%. On the other hand, the marginal effect of water is -0.0324 in the FR column, indicating that each additional day of water disruption decreases the probability of being "fully recovered" by 3.24%.

Figure 7 graphically displays the predicted probabilities on the three recovery outcomes. The computed values are reported in Table 5. Overall, the patterns of each recovery level are shown to be very similar across different types of utility disruptions. The likelihood of being not well recovered (NR) increases with longer days of disruptions, while the likelihood of being fully recovered (FR) decreases. Again, water supply displays the most pronounced effect. The predicted probability of "FR", indicated by the line with squares, is 0.425 for households who never lost water supply. However, the probability decreases rapidly to 0.045 at 20 days without water and to almost 0 at 50 days. The predicted probability of "NR", indicated by the line with circles, is nearly the mirror image. It begins at 0.085 at no disruption and ends at 0.999 at 50 days of disruptions. The probability of "almost recovered" is nonlinear, as indicated by the line with triangles. It begins at 0.489, increases to 0.574, and then decreases to almost 0.001. The effect of water disruption on "almost recovered" is initially

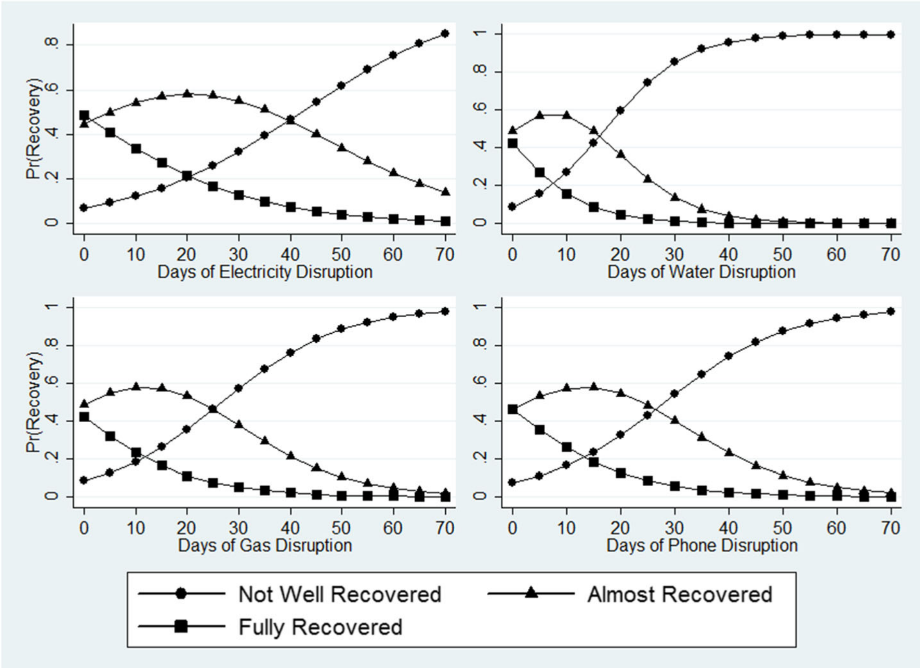

Fig. 7 Predicted probability on recovery level by types of utility disruption

positive and then negative. This occurs because as days increase without water supply, more households are likely to move from category FR to AR than move from AR to NR; consequently, the probability of AR increases. When the days of water disruptions become longer, more households leave AR for NR than enter AR from FR, resulting in a decrease in probability.

Next, we examine the role of household characteristics in explaining the determinants of households' damages and recovery performance. The preparedness model accounts for 6.5%

Table 5 Predicted probabilities on recovery level by types of utility disruption

Variable	Mean	Std. Dev	Min	Max
Predicted possibilities for Recovery=1 (NR)				
Electricity	0.426	0.277	0.067	0.856
Water	0.734	0.337	0.085	0.999
Gas	0.604	0.332	0.085	0.980
Phone	0.586	0.338	0.073	0.978
Predicted possibilities for Recovery=2 (AR)				
Electricity	0.418	0.156	0.133	0.585
Water	0.198	0.231	0.001	0.574
Gas	0.300	0.221	0.019	0.583
Phone	0.306	0.218	0.021	0.583
Predicted possibilities for Recovery=3 (FR)				
Electricity	0.156	0.154	0.011	0.487
Water	0.068	0.125	0.000	0.425
Gas	0.097	0.132	0.001	0.425
Phone	0.108	0.145	0.002	0.464

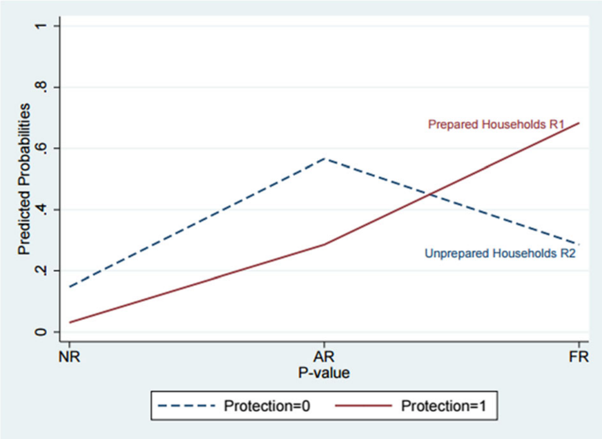

Fig. 8 The role of installing window protection on recovery. Notes: This figure presents the predicted probabilities on household recovery levels with and without wind resistant windows. NR is the level of "Not Recovered", AR is the level of "Almost Recovered" and FR is the level of "Fully Recovered"

of the variance of recovery outcome, according to column (6) in Table 3. Having an insurance policy is found to positively affect household recovery, but it became insignificant when controlling for other variables in the full model (see column 4). This might be caused by the inability of the insurance companies, as we surveyed households eight months after Sandy while receiving insurance claim payment usually takes a longer time, especially during a hurricane event. There might be delays for insurance companies to handle many cases simultaneously, and businesses were also expected to experience interruptions due to Sandy. Damage appears to be positively significant in the full model (see column 3). This is possible because people who hold insurance to cover disasters usually live in an area where frequent disaster occurs. Another possible explanation is that if households realize that they can have their damages covered during a hurricane, they may overestimate the damages and put less effort in preventing their properties due to the "moral hazard" problem. Window protection is

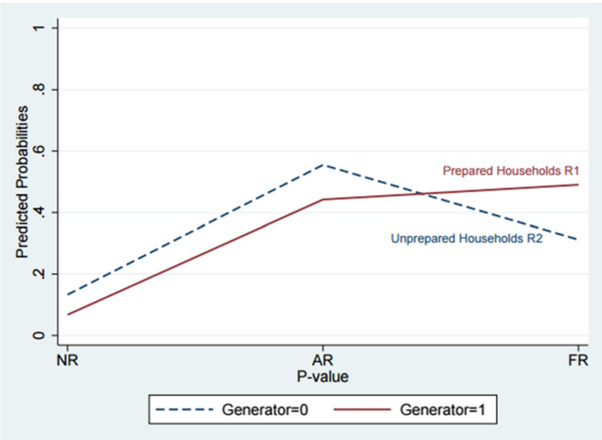

Fig. 9 The role of owning a generator on the recovery. Notes: This figure presents the predicted probabilities on household recovery levels with and without a generator. NR is the level of "Not Recovered", AR is the level of "Almost Recovered" and FR is the level of "Fully Recovered"

positively significant in both damage and recovery level, indicating that households who installed window protections are more likely to report monetary damage, but are also more likely to recover rapidly from those damages. This is possible because households who had window protections may reside in an area severely impacted by Sandy. However, engaging in self-protective actions may also contribute to a higher level of resilience. Figure 8 presents the predicted probabilities on household recovery with and without window protection. As indicated, prepared households (R1) are more likely to achieve the "fully recovered" level compared to unprepared households (R2), providing empirical supports to our framework. Owning an electric generator is found to be significant in the full model (see column 4). Households who had a generator are quicker in recovering. As presented in Fig. 9, having a generator in preparing for Sandy has contributed to a higher probability of "fully recovered" level for prepared households (R1), and unprepared households (R2) yield a lower probability due to their lack of self-protective behaviors.

Socio-economic characteristics are found to be important determinants of household damages and recovery. Consistent with the literature, households with elderly and larger family size and longer years of residence are more likely to report damages caused by Sandy. Educational attainment is found to be significant and positive in both stages. An educated household is more likely to have suffered from damages (due to wealth effect), but is also more likely to recover from those damages quickly. We did not find significant evidence to support that living in a flood zone will increase the probability of incurring damage or lower the speed of recovery in the full model. However, locating in the flood zone is found to have a significantly negative relationship with higher recovery in the Socio-economics model, which accounts for 7.1% of the variance of recovery outcome per column (7) in Table 3. We have also included the state-level dummy variables to study the influence of state differences. Using the state of Connecticut as the base group, we find a significant difference in household damages among different states, while we did not find any evidence to show the differences in recovery levels among them. One of the possible explanations is that more than 80% of respondents at the second stage of the survey are from New York and New Jersey so that the model cannot predict enough variations in recovery across different states.

Table 6 Predicted probabilities for estimated household recovery by Irene experience and education

Irene=0	NR	AR	FR
Less than high school	0.558	0.391	0.052
High school	0.387	0.516	0.098
Some college	0.239	0.582	0.179
Bachelor's degree or higher	0.136	0.561	0.304
Irene=1	NR	AR	FR
Less than high school	0.335	0.545	0.120
High school	0.201	0.585	0.214
Some college	0.112	0.536	0.353
Bachelor's degree or higher	0.059	0.420	0.522
Change from Irene=0 to Irene=1	NR	AR	FR
Less than high school	-0.223	0.154	0.068
High school	-0.186	0.069	0.116
Some college	-0.1127	-0.046	0.174
Bachelor's degree or higher	-0.077	-0.141	0.218

Past experience from Hurricane Irene plays a role in prompting households to a higher recovery level. This result is in line with previous findings that experience and knowledge are important factors. Table 6 presents the predicted probabilities of each recovery level by different types of households, based on their hurricane experience and education, while holding other characteristics constant at the mean. If we look at only households without past hurricane experience (Irene = 0), their recovery level differs with educational attainments. Households with an advanced bachelor's degree or higher have higher likelihood of being "resilient households". We can also examine the role of hurricane experience. For example, the likelihood of being "fully recovered" is increased, and the likelihood of being "not well recovered" is decreased, by gaining hurricane experience (from Irene = 0 to Irene = 1). Among all the households, the highest predicted probability (0.522) of being a "resilient household" is associated with those who have a bachelor's degree or higher and have hurricane experience. On the opposite, the highest predicted probability (0.558) of being a "fragile household" is associated with those who have less than a high school degree and have no hurricane experience.

Overall, we have found evidence to support that utility disruptions are indeed important determinants of long-term household recovery. The findings from the full model further suggest that even after controlling for household characteristics, utility disruptions have significant effects. Just as important, the effects of preparedness activities are positive, indicating that effective self-protective actions and available alternative resources can improve household resilience. Furthermore, household's ability to quickly recover is associated with socio-economic characteristics, such as education and past hurricane experience. These empirical findings from regression analyses therefore substantiate our dynamic framework of household resilience.

Conclusion

Hurricane Sandy has provided us an avenue to observe the role of utility disruption in the affected areas. A disastrous event like hurricane Sandy may not be treated as an occasional incident but rather one that we should expect more frequently due to the exacerbated impact of climate change and sea level rise (Knutson et al. 2010; Nicholls and Cazenave 2010). Special attention should be given towards understanding the hurricane impacts in general and specifically the role of utility disruptions on the household-level recovery processes in particular. In this paper we present a detailed analysis of the determinants of household recovery in the aftermath of Hurricane Sandy. We use responses collected through a household survey, in which households were first asked to report the nature and extent of hurricane-induced damages. Households who reported a positive amount of damages were asked to rate their recovery levels at the subsequent stage.

The major findings suggest that Hurricane Sandy had long-lasting effects on households in the affected areas, especially in the state of New York and New Jersey. Those who have suffered from longer utility disruptions are more likely to report hurricane-induced damages and have had more difficulties in recovering. By comparing the marginal effects and predicted probabilities from our empirical analyses, we find that electricity disruption has the largest effect that increases the likelihood of household damages, and water supply is the most critical utility service at the recovery stage. Effective preparation measures such as installing window protection and having electric generators have led to positive results in reducing adverse shocks. Households with past hurricane experience and higher educational attainments are associated with faster recovery performance. This finding is in line with the literature that education, whether measured by years of schooling or highest degree attained, is associated with a higher level of resilience over the longer term (Frankenberg et al. 2013). Besides education, prior disaster experience is another key driver determining preparedness behavior and increasing household disaster resilience (Hoffmann and Muttarak 2017).

One major contribution of the paper is that we explore the role of utility disruption on household-level recovery based on a framework of household disaster resilience. This topic has not been sufficiently covered in the previous literature and we hope that the analytical framework and the empirical specifications used here can be applied to study the impact of utility disruptions on household recovery following a natural or man-made disaster. The results shed light on the fact that public utility supply following a disaster is crucial to households in the affected areas and policy attention is warned for ensuring the rapid restoration of infrastructures to reduce the adverse impacts. Our framework also considered the cost of preparedness in the framework, which has not been discussed in the previous literature. In general, households tend to take preparation actions stemming from their higher risk perceptions and awareness. However, for those households who had higher risk perceptions but did not engage in preparation activities, the cost of preparation is the likely reason to blame for. These activities are usually costly and therefore influence household decisions due to income effect. Research has shown that socio-economic characteristics are key factors in household preparation decisions. For instance, households with higher socio-economic status (e.g., high-income households) are better prepared and more likely to be insured against disasters (Mozumder et al. 2009; Tierney et al. 2001). If the cost of preparedness is bounded by households' income constraints, it may play an important role in household decisions and responses facing a disaster. Therefore, our findings suggest that policy actions targeted to influence self-protective behavior, such as insurance premium discounts or discounts on alternative resources (i.e., offering discounts for purchasing generators in hurricane-prone areas), can be useful. Also, sharing analysis-based information from previous hurricanes can be utilized to educate self-protecting behavior (disaster preparation, evacuation, applying for post-disaster assistance, etc.) to enable households better cope with disasters. Furthermore, locating the most vulnerable people (such as elderly and large family and ethnic minority groups) within communities is an important step toward effective disaster management.

In the end, there are a few limitations of this paper, and future research is expected to overcome these issues to continue exploring the role of utility disruptions in the presence of hurricanes. For example, the self-reported survey data is always subject to household subjectivity. We also acknowledge that all survey data suffers from memory issues. More accurate information, including the area and the number of days of service interruption, might be collected from public utility agencies as they become available at the household level. Incorporating data from public utility agencies will also enable us to study the role of interdependencies among infrastructures, as the utility disruptions are dealt with separately in our current analysis. Furthermore, we had a relatively small sample size in the second stage of the survey, as we tend to focus on households who suffered from monetary damage to their property. However, hurricane impacts are not limited to property damage, future study should include households who incurred the loss of wage, loss of education, medical expenses, and other types of tangible and intangible damages. It will also be useful to look at county-fixed, instead of state-specific effects, to better capture adaptation heterogeneity across specific locations. Despite these limitations, we hope that this paper contributes to the limited empirical evidence on the impact of utility disruptions in the natural hazard literature and provides useful insights for promoting disaster resilience at the household level.

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Data Availability (data transparency): data will be made available upon reasonable request subject to compliance with IRB guidelines.

Code availability (software application or custom code): code will be made available upon request.

Declarations

Conflicts of interest/Competing interests (include appropriate disclosures): authors declare no conflict of interest.

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