Economics of Disasters and Climate Change (2024) 8:235–261
https://doi.org/10.1007/s41885-024-00145-5

RESEARCH

Hurricane-Induced Power Disruptions: Household Preferences for Improving Infrastructure Resilience

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Received: 10 August 2023 / Accepted: 23 February 2024 / Published online: 27 March 2024

Abstract

In recent years, the increase in the frequency and intensity of hurricanes has posed a significant threat to coastal infrastructures, particularly the electricity supply system. In response to these challenges, several policies have been proposed to improve the resilience of electricity systems, specifically focusing on expediting the restoration of disrupted utilities. However, implementing these resilience plans comes with considerable costs, which must be balanced against the potential benefits experienced by households. This study examines the willingness of Florida residents to financially support the improvement of the electricity infrastructure resilience in response to hurricanes in Florida. We conduct a Discrete Choice Experiment involving 1138 Floridians to assess their willingness to pay for different scenarios aimed at improving electricity system resilience. Three panel mixed logit models are estimated, accounting for preference heterogeneity. Results indicate that the annual welfare estimates per individual range from \$525.51 to \$604.70 across the restoration scenarios. The findings offer compelling evidence, indicating strong support for minimizing hurricane-induced power disruptions by implementing the proposed resilience programs in Florida.

Keywords Discrete choice experiment · Hurricanes · Electricity system · Power disruptions · Resilience · Willingness to pay

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Introduction

Hurricanes have the potential to cause substantial damages and disruptions to the public utility systems, including electricity, transportation, telecommunications, as well as drinking water and wastewater infrastructures (Kwasinski et al. 2006; Campbell and Lowry 2012; Sajadi 2019). The strong winds, storm surges, heavy rainfall, and flooding associated with hurricanes often lead to widespread power outages, affecting a large number of residents in affected areas. These power outages and interruptions can last from a few hours to several days and weeks, depending on the severity of the hurricane. The duration of these outages has profound impacts on various sectors, including businesses, manufacturing, transportation, other utility supply, healthcare, and emergency services (Campbell and Lowry 2012; FEMA 2017; Zimmerman et al. 2017).

The economic impacts of hurricane-induced power outages in the United States are substantial, with estimated losses ranging from \$20 to \$55 billion annually (Campbell and Lowry 2012). The growing trend of extreme weather-induced electricity outages, and their cascading impacts indicate the increasing vulnerability to these events. In addition to power disruptions, hurricanes can also disrupt other essential utility services such as drinking water treatment and wastewater systems, leading to potential water supply crises (Duffy 2013; Zimmerman et al. 2017; Matthews 2016). Hurricanes have the potential to cause severe damage to critical transportation infrastructure, including roads, bridges, and transportation networks. The combined impact of hurricane-induced flooding, fallen trees, and downed transmission and distribution lines often leads to road closures, impeding the repair process and making transportation and other related services inaccessible. Finally, hurricanes can inflict substantial damage on telecommunication networks through hurricane-induced power outages. These outages can disrupt access to essential communication services such as telephones and the internet. Consequently, this disruption can hinder communication with individuals in need of urgent help or medical care (Kwasinski et al. 2006).

Florida has experienced a series of devastating hurricanes in recent years, making it one of the most vulnerable regions to these catastrophic events. The frequency of hurricanes in Florida is particularly notable, with the state being impacted by an average of one hurricane every two years and a major hurricane every four years (Malmstadt et al. 2009). In the span of just two years, Florida faced significant devastation from a series of major hurricanes. In 2004, the state was hit by four major hurricanes: Charley, Frances, Ivan, and Jeanne (Baker 2011). The following year, Florida experienced the impact of two more major hurricanes: Dennis and Wilma (Baker 2011). Among these, Hurricane Wilma stands out as one of the most destructive storms since Hurricane Katrina in 2005. It made multiple landfalls and caused widespread damage throughout Florida, resulting in over 3 million electricity outages (Chatterjee and Mozumder 2015).

In recent years, Florida faced the impact of several devastating hurricanes. In 2016 and 2017, the state was hit by a series of powerful storms. In 2016, Hurricanes Hermine and Matthew struck Florida, followed by Hurricane Irma in 2017 (Florida Public Service Commission 2018). Hurricane Irma, which made landfall as a Category 3 hurricane in the Florida Keys and as a Category 4 hurricane in southeastern Florida on September 10, 2017, had a profound impact. The hurricane's high-speed winds and heavy rainfall left approximately 6.5 million customers without electricity, disrupted access to potable water, and resulted in an estimated \$50 billion in damages in the United States. This made Hurricane Irma the fifth costliest hurricane in U.S. history (Issa et al. 2018; Cangialosi et al. 2018). Given the intensified risk posed by these extreme weather events, critical infrastructures are now more vulnerable than ever before. It becomes crucial to prioritize resilience as a vital factor in protecting these infrastructures and the coastal communities relying on them (NIAC 2009).

Critical infrastructure resilience can be defined by considering three key factors: robustness, resourcefulness, and quick recovery (NIAC 2009). Robustness refers to the capacity of critical infrastructures to maintain their critical operations even when faced with disasters. Resourcefulness is defined as the capacity to respond and cope effectively as a disaster expands. Quick recovery signifies the capability to quickly return to normal operations after an interruption caused by a crisis. Infrastructure resilience, as defined by NIAC (2009), is the ability to minimize the impact and duration of disruptive events. The efficacy of a resilient infrastructure hinges on its capacity to foresee, absorb, adjust to, and recover quickly from potential disruptions.

In response to the impact of climate change and extreme weather events on critical infrastructure, substantial efforts have been undertaken in recent years to enhance the resilience of vital infrastructure systems, including electricity in Florida. After the devastating hurricane seasons of 2004 and 2005, the Florida Public Service Commission initiated a series of programs aimed at strengthening the state's electricity infrastructures. These programs included measures such as the hardening of electrical transmission and distribution lines, improved vegetation management, and the strategic placement of electrical lines underground. The primary objectives of these initiatives were to mitigate hurricane related damages, shorten restoration times, lower restoration costs, and enhance the overall reliability (Campbell and Lowry 2012; Florida Public Service Commission 2008, 2018).

The Commission also requested investor-owned electric utilities (IOUs) to periodically renew their hurricane hardening strategies and provide updated plans every three years. These continuous hardening efforts have proven to be instrumental in enhancing the resilience of the electricity infrastructure over the past few years. The effectiveness of the hardening plans was put to the test during the 2016 and 2017 hurricane seasons. In 2018, the Commission reported that the utilities that had undergone hardening performed better than the non-hardened ones (Florida Public Service Commission 2018). Furthermore, in October 2019, the Florida legislature passed Storm Protection Plans (SPP) cost recovery Bill 786, which was subsequently signed into law by the Governor. Accordingly, the Florida Public Service Commission mandates IOUs to develop 10-year restoration plans and update them regularly. These plans (i.e., SPPs), build upon the strategies that IOUs have been implementing since the 2004–2005 hurricane seasons to enhance the resilience of electricity infrastructures. Regulators have recognized the benefits of SPPs, as they contribute to reducing the extent and duration of power outages and the associated restoration costs, ultimately benefiting electricity customers (Walton 2020).

However, implementing these resilience plans comes with considerable costs, which must be balanced against the potential benefits experienced by households from having a resilient electricity transmission and distribution infrastructure. Despite the efforts to enhance the resilience of electricity systems in Florida, little is known about Floridians' preferences and their perceptions regarding improvements in the resilience of electricity systems in response to hurricanes. Hence, exploring household perceptions about these resilience plans can provide decision-makers with valuable insights regarding residents' preferences and the potential benefits of resilient infrastructure for utilities. Moreover, by aligning resilience strategies with household preferences and support, decision-makers can devise effective pricing plans to generate sufficient funding for future projects.

The key aspect within this context is assessing household willingness to pay (WTP), as this measure plays an important role in determining the feasible level of investment for strengthening the electricity system (Baik et al. 2020). In essence, WTP helps determine the financial contribution households are willing to make towards securing and improving the electricity systems. It also sheds light on the anticipated benefits they expect to receive from minimizing potential negative impacts of disruptions caused by hurricanes.

The primary objective of this study is to investigate public preferences and WTP for improving the resilience of electricity infrastructures in Florida, particularly in response to hurricanes. To achieve this goal, we conducted a discrete choice experiment (DCE) as part of a "household survey on the socioeconomic, health, political, and environmental aspects of Hurricane Irma in Florida." Following the framework proposed by NIAC (2009), resilience in this study is defined as the ability to shorten the time required for restoring disrupted electricity utilities and providing services to a higher percentage of customers within specific days following a hurricane event.

This study makes significant contributions to the literature in two ways. First, to our knowledge, this is the first study that applies a DCE approach to investigate households' preferences and WTP for improving the resiliency of power infrastructures in response to hurricanes in Florida, one of the most hurricane-prone regions in the whole world. Second, this study provides decision-makers with essential information that enables them to make more effective investments in resilience programs in response to coastal hazards in vulnerable communities in the State of Florida and beyond.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the literature on improving the resiliency of critical infrastructures to climate risks and extreme weather events. Section 3 outlines the DCE approach involving discrete choice modeling and design. Section 4 presents the survey and data collection process. In Section 5, we discuss the main findings of the study, and in Section 6, we provide concluding remarks and implications of the research.

Literature Review

There is a body of research exploring the WTP of both households and manufacturing firms to avoid short term and long term outages in electricity and water supply using Contingent Valuation method (CVM) and DCE approaches (Del Saz-Salazar et al. 2016; Appiah et al. 2019; Cooper et al. 2019; Ozbafli and Jenkins 2016; Ghosh et al. 2017; Kim et al. 2018; Morrissey et al. 2018; Amoah et al. 2019; Carlsson et al. 2020; Wen et al. 2022). However, few studies have analyzed preferences for enhancing the resiliency of critical infrastructures in response to extreme weather events such as hurricanes, cyclones, floods, and cold waves. For instance, Baik et al. (2020) examined customers' WTP for improving the resilience of electricity systems during very cold winters using a CVM. In this case, resilience was defined as providing back-up power services during long-term power outages. Their findings indicated that customers in the Northeastern U.S. were willing to pay more to support collective power backup services than sustaining their own private backup services.

In the context of hurricane events, Wang et al. (2018) used a DCE to assess public preferences for enhancing the resilience of transportation systems in New York City.

Their definition of resilience focused on reducing the time required to restore disrupted transportation systems. The DCE included two hypothetical scenarios of improvements in the resilience of transportation infrastructures, alongside a status quo scenario. These scenarios are differentiated based on the level of operational improvement in the transportation system within specific time frames: 1–3 days, 4–6 days, 1 week, and 2 weeks. Using mixed logit models, they found that respondents' WTP to improve system resiliency falls within the range of $75 to $450 per year. These findings provide strong evidence of support for funding resilience programs in New York City's transportation systems.

In a study focusing on flood events, Price et al. (2019) explored public preferences for enhancing water supply infrastructure in Canada to mitigate the risk of flooding, flood-related boil water advisories, and flood-related power loss. Employing the random-effects probit model, they found that households exhibited a substantial WTP for a policy program that effectively addresses flood risks. Additionally, the researchers identified significant heterogeneity across different regions and sociodemographic groups. Notably, residents in rural areas and those living in regions with higher housing value demonstrated a higher WTP for the proposed policy programs. In a study focusing on cyclone events, Islam et al. (2019) employed a CVM to assess household WTP for enhancing the resilience of drinking water systems in Southwestern Bangladesh. The findings revealed a positive response from most households, as they demonstrated a positive WTP for the implementation of cyclone resilient drinking water systems. The mean WTP amounted to 263 Taka/month (approximately 1 US$ =110 Taka), indicating the value they placed on improved resilience. Notably, the primary factor influencing household' WTP was the accessibility to functional water sources. This suggests that households experiencing limited access to reliable water sources were more likely to support the development of resilient water systems.

In a recent study, Maldonado et al. (2023) employed a CVM to investigate public preferences for enhancing water supply continuity during extreme weather conditions in the Metropolitan Region of Chile. The results revealed significant heterogeneity among consumers, with the mean WTP varying from USD 1.09 to USD 5.79 per month. Additionally, the study identified political views as one of the most influential factors determining respondents' WTP. Lastly, a growing body of literature also addresses man-made risks. For instance, Rulleau (2023) utilized a DCE method to explore preferences for enhancing the resilience of water distribution systems to cyber-attacks in France. The present study contributes to this growing body of literature by investigating customer preferences for enhancing the resilience of electricity infrastructure to hurricanes in Florida. By means of a DCE approach, we assess the extent of support from Florida residents for funding resilience programs in electricity infrastructures using a specific payment mechanism.

Discrete Choice Experiment

DCEs were originally employed in the fields of transportation and marketing, where they were used to analyze trade-offs between different attributes of transportation projects and private goods. Over time, DCEs have also gained prominence in environmental economics to value non-market goods and services (Alpizar et al. 2001).

In DCEs respondents are presented with multiple choice sets, each containing various hypothetical alternatives. These alternatives are defined by levels of different attributes (e.g., price, quality) and if a price or cost attribute is included, marginal WTP values for other attributes can be estimated. When choosing one of the alternatives, respondents implicitly make trade-offs between different attribute levels, allowing researchers to identify the marginal value of the attributes and levels (Alpizar et al. 2001).

Modeling

The response to the choice between alternatives can be effectively demonstrated within a Random Utility Maximization (RUM) framework. This model assumes that respondents select the alternative that maximizes their utility. This model is also based on the hypothesis that respondents know and are certain about their utility, but researchers are not able to detect or observe the respondents' utility. Thus, there exist unobservable factors that are captured in a random error term. The overall utility that respondent k derives from selecting alternative i from choice set t can be written as (McFadden 1974; Ropars-Collet et al. 2017; Holmes et al. 2017):

$$U_{kit} = V_{kit} + \varepsilon_{kit} = \beta_k' x_{kit} + \varepsilon_{kit}, k = 1, \ldots, N \tag{1}$$

Based on Eq. (1), the utility is the sum of a systematic component (V) and a random component (ε). In Eq. (1), β_k is a vector of preference parameters to be estimated, x_{kit} represents a vector of attribute levels, and ε_{kit} is the error term.

The underlying assumption in applying a RUM model is that the error terms are independently and identically distributed (IID). This assumption induces a logistic distribution, leading to the multinomial logit (MNL) model (Holmes et al. 2017). Given that a choice set contains I alternatives, the probability of respondent k selecting alternative i in choice set t is given by:

$$P_{kit} = \frac{\exp\left(\beta_k' x_{kit}\right)}{\sum_{i=1}^{I} \exp\left(\beta_k' x_{kit}\right)} \tag{2}$$

The MNL model is widely used for its simplicity in estimation; however, it is subject to two limiting assumptions. Firstly, it assumes that the alternatives are independent, and secondly, it imposes restrictions on modeling variations in preferences among respondents. The first assumption leads to the Independence of Irrelevant Alternatives (IIA) property, which states that changes in the alternatives do not affect the ratio of chances of choosing between any two alternatives in a choice set. If this assumption is not met, the MNL model should not be applied. The second limitation relates to dealing with observed and unobserved heterogeneity. Observed heterogeneity can be incorporated into the model by introducing interaction terms between sociodemographic characteristics and attributes. However, the IID assumption is highly restrictive regarding unobserved heterogeneity (Alpizar et al. 2001; Holmes et al. 2017).

The MNL model can be extended to address its limitations, such as capturing preference heterogeneity (Holmes et al. 2017). An advanced extension of the MNL model is the

Panel Mixed Logit (PML) model, also known as random parameter logit. The PML model assumes that parameters can vary randomly across respondents. Additionally, it explicitly considers correlation across repeated choices made by each respondent (Revelt and Train 1998). In the PML model, the probability of respondent k selecting alternative i in choice set t can be defined as the integral of the MNL probability over the distribution of β_k (Train 2009):

$$P_{kit} = \int P_{kit} f\left(\beta_k | \theta\right) \mathrm{d}\beta_k \tag{3}$$

where $f(\beta_k|\theta)$ is the density function of β_k described by a vector of parameters θ.

If utility is a function of a price or cost attribute, DCEs allow to calculate WTP values for welfare gains resulting from alterations in the attribute levels. (Holmes et al. 2017).

Assuming a linear utility function, the WTP for a marginal change in the level of attribute A is given by the negative ratio of the parameter for attribute A (β_A) to the parameter for the price attribute (β_p) (Holmes et al. 2017):

$$WTP_A = -\frac{\beta_A}{\beta_p} \tag{4}$$

Indeed, the marginal WTP (which is also known as implicit price) displays how much respondents are willing to pay for a marginal change in the attribute (Ropars-Collet et al. 2017; Holmes et al. 2017).

Furthermore, we calculate the compensating surplus (CS) for various improvement scenarios, which involve combinations of different restoration levels. Following Holmes et al. (2017), we define it as:

$$CS = -\frac{1}{\beta_p}\left(V_1 - V_0\right) \tag{5}$$

where β_p is the price parameter; V_1 is the utility after a scenario or program is implemented, and V_0 is the initial utility (Holmes et al. 2017).

Experimental Design

To design our DCE, we carefully selected five attributes that capture key features of resilient electricity infrastructures. We chose these attributes in collaboration with experts from the electricity sector and based on insights from the existing literature. Following Wang et al. (2018), each choice set in our DCE comprises two hypothetical alternatives for improving the resilience of the electricity infrastructure (Option A and Option B) and a status quo alternative. In this context, resilience is defined as the ability to restore disrupted electricity services in a reduced time frame and to provide services to a higher percentage of customers within a specific period.

Accordingly, each alternative has four attributes that demonstrate the enhancement of electricity infrastructure resilience in terms of the percentage of customers receiving power supply within specific timeframes following disruptions caused by a severe hurricane event, such as Hurricane Irma. These timeframes consist of 1–3 days, 4–6 days, 1 week, and 2 weeks after the hurricane event. In the DCE respondents were presented with the cumulative percentage of customers receiving power in each timeframe; for example: 40%

Table 1 Attributes and levels for improving the resilience of electricity infrastructure

Attributes	Levels
Percentage of electricity customers receiving the power service restored in 1–3 days after a strong hurricane.	10%, 20%, 30%, 40%, 50%
Percentage of electricity customers receiving the power service restored in 4–6 days after a strong hurricane.	20%, 30%, 40%, 50%, 60%
Percentage of electricity customers receiving the power service restored in 1 week after a strong hurricane.	40%, 50%, 60%, 70%, 80%
Percentage of electricity customers receiving the power service in 2 weeks after a strong hurricane	60%, 70%, 80%, 90%, 100%
Fee for improvement in the resilience of electricity infrastructure (defined as an increase in annual electricity bill)	\$0, \$60, \$80, \$100, \$120, \$140, \$160,

within 1–3 days, 50% within 4–6 days, 70% within 1 week, and 80% within 2 weeks. Customers whose power was not restored during these timeframes were assumed to experience a power outage of more than two weeks (i.e., power was restored at an unspecified time more than two weeks after the hurricane event). This category of customers—those receiving power after two weeks—serves as the reference category in the analysis.

While respondents were presented with the cumulative percentages of customers receiving power, we used the incremental improvement between timeframes in the statistical analysis.[1] Thus, estimated parameters for power resilience attributes indicate the utility associated with a marginal increase in the percentage of customers receiving power in a timeframe relative to the reference category of more than two weeks. Subsequently, we were able to obtain WTP values for marginal increases in percentages of customers recovered, providing valuable insights into the degree of support for a faster restoration of electricity supply.

To facilitate the improvement in the resilience of electricity infrastructure, we introduced two hypothetical alternatives, both of which include a funding mechanism. For this purpose, we asked the respondents to consider the proposal of the "Power Resiliency Fund" (PRF) initiated by the Florida State Government. The PRF aims to enhance and support the resiliency of electricity infrastructures in preparation for future hurricanes, thereby minimizing damages, outages, and recovery time for customers. Under this hypothetical funding mechanism, respondents were asked to indicate their willingness to support the PRF through an annual payment. The specific amount of money they would be willing to contribute (depending on the attributes and their levels in the alternatives) would be added to their annual electricity bill for a duration of 10 years. (For more detailed information, see the appendix).[2] Table 1 displays the attributes and their levels used in designing the choice sets for the study.

We generated 16 choice sets, each containing 3 alternatives representing various levels of resilient electricity attributes. To construct the electricity restoration choice sets

[1] For example, cumulative percentages of 40% in 1–3 days, 50% in 4–6 days, 70% in 1 week, and 80% in 2 weeks are coded as 40% in 1–3 days, an additional 10% in 4–6 days, an addition 20% by 1 week, and an additional 10% by 2 weeks.

[2] It is important to note that to mitigate potential hypothetical bias, respondents were presented with a realistic payment mechanism and a reminder of their budget constraints.

	**Current Situation (% of households with electric power)**	**Option A for Improving Resiliency in Electric Power Supply (% of households with electric power)**	**Option B for Improving Resiliency in Electric Power Supply (% of households with electric power)**
1-3 days after 	20%	30%	40%
4-6 days after 	20%	30%	40%
1 week after 	40%	60%	70%
2 weeks after 	80%	90%	100%
The payment to **Florida Power Resiliency Fund (FL-PRF)** as an **annual increase in your electricity bill for next 10 years**	0$	120$	160$

Fig. 1 Sample choice set for improving the resilience of electricity infrastructures

that provide us with the most precise parameter estimates in the analysis, we adopted a Bayesian D-optimal design approach. Because choice models are nonlinear in the parameters, the efficacy of the design hinges on the unknown parameters. Bayesian designs provide a solution to this issue as they are optimized over a prior distribution of possible parameter values. This distribution takes the form of a multivariate normal distribution, denoted as $N(\beta|\beta_0, \Sigma_0)$, where β_0 represents the prior mean and Σ_0 is the prior variance-covariance matrix. Bayesian optimal designs exhibit robust performance across a wide range of parameter values by effectively dealing with uncertainties related to the specified parameters (Kessels et al. 2011). For the 3 options in each choice set, we incorporated the restriction that option B had the same or higher levels than option A, which in turn, had the same or higher levels than the status quo. We split the 16 electricity choice sets into 8 groups, where each respondent was randomly assigned a group of 2 choice sets. We created the Bayesian D-optimal design using JMP Pro 16 software. Figure 1 illustrates a sample of a hypothetical electricity restoration choice set presented to the respondents.[3]

Survey and Data Collection

The survey was structured into three sections. In section one, we introduced the purpose of the questionnaire and collected data on the socioeconomic characteristics of the respondents. This included age, ethnicity, level of education, gender, marital status, political identity, and household income. Section two focused on understanding respondents' experience with Hurricane Irma and their decisions regarding evacuation. We investigated experiences during hurricanes in general and perceptions of utility disruptions. Additionally, we explored concerns regarding future hurricanes and views on funding mechanisms employed to enhance the resilience of electricity infrastructure in preparing for such risks. In section three, we presented the respondents with the choice sets designed to assess their preferences for power infrastructure resilience and service restoration after a hurricane event.[4]

The online questionnaire was administered through Qualtrics and conducted from September 2020 to early December 2020. Prior to the main study, a pilot survey was conducted in September 2020 to refine the questionnaire and ensure its effectiveness. A total of 1138 responses were collected from the final sample (excluding pilot surveys) by December 2020.[5] It is important to note that our survey was conducted during the hurricane season in Florida in 2020. The timing of the survey administration during this specific period allowed us to capture respondents' perceptions and attitudes towards infrastructure resilience in a context where and when the threat of hurricanes was more prominent. However, it is essential to acknowledge that the results obtained during the hurricane season would not necessarily be the same if the survey had been conducted during the non-hurricane season.

Data summary of the 16 electricity choice sets revealed that among the respondents, 34% chose plan A, 44% chose plan B, and 22% chose the status quo option. These results indicate a higher preference for plan B compared to plan A and the status quo option. The distribution of choices for each choice set is reported in Table 2. The descriptive statistics

[3] We compared models that simultaneously estimated separate parameters for choice task 1 and choice task 2. We then tested for differences in estimated parameters and WTP values across tasks. Wald tests showed no significant differences between parameters (i.e., SQASC, cost attribute, time-to-restoration attributes) or WTP values. These results suggest that respondent's hypothetical behavior does not meaningfully differ between the two choice tasks.

[4] In the survey, we highlighted the area impacted by Hurricane Irma, specifically the whole state of Florida, and noted that the majority of residents in Florida were affected by the hurricane.

[5] For the PML model, we limited the analysis to respondents with complete socioeconomic information and respondents living in single-family homes, condos, duplexes, and townhomes. Respondents living in apartments were excluded from the analysis.

Table 2 Frequency distribution of resilience for power infrastructure choice sets

Power Choice Set	Alternative	Freq.	Percent
Survey Version 1: Choice set 1			
	Plan A	46	32.62
	Plan B	61	43.26
	Status quo	34	24.11
	Total	141	100
Survey Version 1: Choice set 2			
	Plan A	46	32.62
	Plan B	60	42.55
	Status quo	35	24.82
	Total	141	100
Survey Version 2: Choice set 1			
	Plan A	46	31.08
	Plan B	69	46.62
	Status quo	33	22.3
	Total	148	100
Survey Version 2: Choice set 2			
	Plan A	53	35.81
	Plan B	60	40.54
	Status quo	35	23.65
	Total	148	100
Survey Version 3: Choice set 1			
	Plan A	49	35.25
	Plan B	64	46.04
	Status quo	26	18.71
	Total	139	100
Survey Version 3: Choice set 2			
	Plan A	46	33.09
	Plan B	62	44.6
	Status quo	31	22.3
	Total	139	100
Survey Version 4: Choice set 1			
	Plan A	43	30.07
	Plan B	65	45.45
	Status quo	35	24.48
	Total	143	100
Survey Version 4: Choice set 2			
	Plan A	64	44.76
	Plan B	56	39.16
	Status quo	23	16.08
	Total	143	100
Survey Version 5: Choice set 1			
	Plan A	54	37.76
	Plan B	56	39.16
	Status quo	33	23.08
	Total	143	100

Table 2 (continued)

Power Choice Set	Alternative	Freq.	Percent
Survey Version 5: Choice set 2			
	Plan A	39	27.46
	Plan B	62	43.66
	Status quo	41	28.87
	Total	142	100
Survey Version 6: Choice set 1			
	Plan A	49	34.75
	Plan B	70	49.65
	Status quo	22	15.6
	Total	141	100
Survey Version 6: Choice set 2			
	Plan A	58	41.13
	Plan B	53	37.59
	Status quo	30	21.28
	Total	141	100
Survey Version 7: Choice set 1			
	Plan A	47	34.81
	Plan B	67	49.63
	Status quo	21	15.56
	Total	135	100
Survey Version 7: Choice set 2			
	Plan A	36	26.67
	Plan B	72	53.33
	Status quo	27	20
	Total	135	100
Survey Version 8: Choice set 1			
	Plan A	49	34.27
	Plan B	65	45.45
	Status quo	29	20.28
	Total	143	100
Survey Version 8: Choice set 2			
	Plan A	58	40.56
	Plan B	53	37.06
	Status quo	32	22.38
	Total	143	100

of the sample are presented in Table 3. As Table 3 depicts, 58% of the respondents were female, and 38% fell within the age range of 30–45 years. Moreover, over 40% of the respondents had educational attainment beyond a bachelor's degree. A similar percentage of respondents reported an average net annual income level ranging between $42,000 and $96,000.

In comparing our sample to the total population of the State of Florida, some differences were notable. The sample consists of a slightly higher percentage of females (58% in

Table 3 Descriptive statistics and definitions of variables used in the analysis

Characteristics	Level	Mean	SD	N
Education	Education [1]: Less than a high school diploma	0.0443	0.2058	1138
	Education [2]: High school degree	0.2099	0.4074	1138
	Education [3]: College degree	0.3339	0.4718	1138
	Education [4]: Bachelor's degree	0.2046	0.4036	1138
	Education [5]: Postgraduate degree	0.2073	0.4055	1138
Age (years)	Age [1]: age > =18 & age < 30	0.2542	0.4356	1138
	Age [2]: age > =30 & age < 45	0.3853	0.4869	1138
	Age [3]: age > =45 & age < 60	0.1683	0.3743	1138
	Age [4]: age > =60	0.1922	0.3942	1138
Net annual income	Low Income: Less than $42,000	0.1391	0.3463	1138
	Medium Income: Between $42,000–$96,000	0.4202	0.4938	1138
	High Income: more than $96,000	0.2987	0.4579	1138
Gender	Gender [1]: Female	0.5846	0.493	1138
Race	Race [1]: White	0.7414	0.4381	1138
	Race [2]: Black or African American	0.1107	0.3139	1138
	Race [3]: Hispanic or Latino	0.1019	0.3026	1138
	Race [4]: Other races (including Native American, Asian / Pacific Islander)	0.0456	0.2088	1138
Political party	Liberal	0.2882	0.4529	1138
	Conservative	0.3224	0.4674	1138
	Independent	0.3892	0.4876	1138
Hurricane Iram-induced power outage	Experienced at least 1 day power outage	0.7322	0.4428	1138
Home ownership	owned	0.5462	0.4981	1138
	rented	0.4538	0.4981	1138
Living in a coastal county	Coastal county [1]: living in a coastal county	0.6499	0.4770	1138

the sample vs. 50% in the population of Florida). In terms of income, the sample exhibits a slightly lower median household income of $57,000 compared to the population median income of $61,777 (in 2021 dollars). Additionally, the sample shows a slightly lower level of racial diversity, with 74% identifying as white compared to 76% in the population, 11% identifying as Black or African American compared to 17% in the population, and 10% identifying as Hispanic or Latino compared to 27% in the population.[6] Some of these differences may be due to the use of different racial and ethnicity categorization schemes in the two data sources. However, it is worth noting that the differences in these socioeconomic characteristics between the sample and the Florida population are not substantial, and the variability is relatively small. Therefore, the data from our sample can still provide meaningful estimates of WTP for resilient electricity infrastructure in Florida.

[6] U.S. Census Bureau, American Community Survey (ACS). For more information, see: (https://www.census.gov/quickfacts/fact/table/floralcitycdpflorida,FL,US/PST045221)

Results

Panel Mixed Logit Model Estimates

We employed PML modeling to assess the respondents' marginal utility obtained from choosing an alternative for improving the resilience of electricity infrastructures. The PML deals with the heterogeneity across respondents' preferences since it assumes that preference parameters vary randomly across respondents (Train 2009).[7] In particular, we modeled the restoration attributes and a status quo alternative specific constant (SQASC) as normally distributed random parameters. The annual payment is modeled using a non-random parameter.

Three distinct PML models are estimated, and the parameter estimates are presented in Table 4. In the first model, we consider only the restoration attributes. The second and third models, however, expand upon the first model by incorporating the effects of socioeconomic characteristics to account for preference heterogeneity. Accordingly, we included interactions between the SQASC and various socioeconomic factors to capture the observed heterogeneity. To capture unobserved heterogeneity, the SQASC was included in the vector of random variables across all PML models.

In Model 1, the *payment* estimate, which represents the marginal utility of money, is statistically significant and has an expected negative sign, indicating that the respondents prefer alternatives with lower payments. The coefficients associated with the restoration attributes (including *power services restored within 1–3 days*, *4–6 days*, *1 week*, and *2 weeks after a hurricane*) are significant and have expected positive signs. Although the magnitude of these coefficients suggests marginal utility declines with the time needed for power restoration (i.e., faster power restoration is preferred), Wald tests indicate there are no significant differences between estimated parameters. The inclusion of the *SQASC* in the model allows us to separate the effect of the restoration alternatives from the status quo option. The negative estimated coefficient on the *SQASC* suggests that the status quo option is associated with lower utility than the restoration alternatives (i.e., option A or option B). In other words, respondents benefit from the upgraded restoration policy regardless of the specific changes in electricity restoration.

Model 2, presented in Table 4, expands upon Model 1 by introducing interactions between the socioeconomic variables (including *income*, *gender*, *age*, and *race*) and the *SQASC* to capture observed heterogeneity in preferences among respondents. The model also incorporates the location of residence via interactions between the *SQASC* and an indicator for living in a coastal county. Like Model 1, all the estimated coefficients associated with the time-to-restoration attributes remain statistically significant and have the expected positive signs. The order of valuation across these attributes is decreasing as expected, but again the differences are not statistically significant.

The estimated coefficient of the *SQASC* in Model 2 provides insights consistent with those of Model 1 regarding the benefits respondents derive from selecting restoration alternatives over the status quo option. The introduction of interaction terms allows us to further explore the influence of socioeconomic factors on preferences. The estimated

[7] In addition to the PML model, we analyzed the choices of our DCE using a latent class model (LCM). In the LCM, populations are assumed to contain a finite number of preference classes; thus, unobserved heterogeneity is modeled with class-specific rather than respondent-specific preferences. The results from a LCM with two classes are reported in the appendix.

Table 4 PML model estimates for improving the power infrastructure resilience

	Model 1		Model 2		Model 3	
	Estimate	SD	Estimate	SD	Estimate	SD
Improvement in power service restored within 1–3 days after a hurricane	0.0664*** (0.0129)	0.0822*** (0.0174)	0.0677*** (0.0136)	0.0850*** (0.0173)	0.0685*** (0.0138)	0.0862*** (0.0174)
Improvement in power service restored within 4–6 days after a hurricane	0.0580*** (0.0169)	0.0615 (0.0594)	0.0611*** (0.0184)	0.1148* (0.0601)	0.0613*** (0.0188)	0.1318** (0.0598)
Improvement in power service restored within 1 week after a hurricane	0.0463*** (0.0134)	0.0415 (0.0536)	0.0473*** (0.0143)	0.0288 (0.0468)	0.0470*** (0.0146)	0.0245 (0.0423)
Improvement in power service restored within 2 weeks after a hurricane	0.0420*** (0.0112)	0.0146 (0.017)	0.0423*** (0.012)	0.0018 (0.0155)	0.0421*** (0.0121)	0.0084 (0.0237)
SQASC	−5.0972*** (0.8119)	7.0525*** (0.9717)	−6.091*** (2.2089)	7.5985*** (1.4683)	−4.4642** (2.2454)	7.7813*** (1.5646)
Payment	−0.0119*** (0.0029)		−0.0119*** (0.0031)		−0.0121*** (0.0031)	
SQASC* medium Income			−2.0862** (0.9229)		−1.9809** (0.9787)	
SQASC* high Income			−2.6976** (1.277)		−2.4214* (1.2679)	
SQASC* Female			2.9498*** (0.9695)		2.9674*** (1.0075)	
SQASC*Age [18–29]			−3.6896*** (1.2285)		−3.6112*** (1.2629)	
SQASC*Age [30–44]			−4.4879*** (1.2845)		−4.3007*** (1.388)	
SQASC*Age [45–59]			−2.6706** (1.2476)		−2.7252** (1.3269)	
SQASC*white			2.5449 (1.594)		2.4046 (1.5297)	
SQASC*African America			1.5271 (1.8124)		1.5893 (1.7934)	
SQASC*other races			4.2835* (2.4656)		4.2005* (2.3503)	
SQASC*coastal county			0.5884 (0.7875)		0.5431 (.8128)	
SQASC*liberal					−2.6049 ** (1.0795)	
SQASC*conservative					−0.4456 (0.8561)	
SQASC*power outage experience					−1.3525 (0.8808)	
Number of Respondents	911		911		911	
Log likelihood	−1686.5193		−1551.6274		−1546.3753	

Standard errors are reported in parentheses. $*p<0.1$, $**p<0.05$, $***p<0.01$

coefficient of the interaction term *SQASC*high income* is negative, significant, and has a higher magnitude compared to the interaction term *SQASC*medium income*. This income effect suggests that as income increases, respondents are more likely to select a restoration alternative.

The estimated coefficient on *SQASC*female* suggests that female respondents are less likely to support the restoration policy.[8] Younger respondents are more likely to support the resilient power infrastructure policy. This may reflect a stronger environmental and climate consciousness among younger respondents. Younger individuals are often more engaged and concerned about environmental issues (Han et al. 2022). Lastly, interaction terms between race attributes and *SQASC* were found to be insignificant except for the interaction term *other race* SQASC*. This implies that compared to Hispanic respondents, Native Americans/Asian/Pacific Islanders are less likely to support the resilience policy. The estimated coefficient on the interaction between the *SQASC* and *living in a coastal county* indicator shows that the likelihood of selecting the status quo option did not significantly differ across regions.

In Model 3, we expand the analysis by incorporating two additional interactions: political party affiliation and experience of at least one day power outage induced by Hurricane Irma, with the SQASC. The signs and statistical significance of the estimated coefficients on the restoration attributes, SQASC, payment, and the interaction terms align with our expectations and are consistent with the results obtained in Model 1 and Model 2. We observe that liberal respondents tend to show greater support for restoration policies compared to those who identify as independent, possibly due to differences in the degree of trust placed in the public sector to implement the proposed program. However, there is no statistically significant difference between individuals who experienced at least one day power outage (induced by Hurricane Irma) and those who did not in terms of supporting the resilience policy.[9]

The standard deviations (SD) of the random parameters are presented in Table 4. Results indicate that the SD of restoration attributes for 1 week and 2 weeks are not statistically significant across all three models. For Model 1, the SD of the restoration attribute for 4–6 days is not statistically significant, but it becomes significant in Models 2 and 3. On the other hand, the SD of the restoration attribute for 1–3 days and the SQASC option is statistically significant in all three models. These findings suggest there is considerable heterogeneity among respondents regarding their preferences for the status quo option and the time-to-restoration attribute in 1–3 days. In contrast, preferences for other restoration attributes show less heterogeneity and tend to be more homogeneous.

[8] It is unclear why female respondents are more likely than males to select the status quo option. One possible explanation is that females, particularly in lower income households, have less agency over household resources and are thus less likely to support a program that increases monthly utility payments. We find some support for this hypothesis in an alternate set of models that included three-way interactions between the SQASC, female respondent indicator, and household income indicators. Results suggest that the difference in female and male choices is substantially more pronounced among low-income households.

[9] We also estimated alternative specifications of Model 2 and Model 3 that incorporated the region of residence via interactions between the SQASC and regional indicators (i.e., Panhandle, North, Central, and South). Model results showed that the likelihood of selecting the status quo option did not significantly differ across regions.

WTP Estimates for Greater Resilience of the Power Infrastructure

We present the marginal WTP estimates or implicit prices for improvements in the resilience of electricity infrastructure. The calculations are based on the results of Model 1 (see Table 4) and derived using Eq. (4). The results in Table 5 show that respondents are willing to pay more for a faster restoration of electricity supply after an extreme hurricane event like Irma. More specifically, these estimates suggest that, for example, on average, each respondent is willing to pay \$5.54 for a 1% increase in the number of customers with power within 1–3 days, relative to power being restored after more than two weeks. Likewise, respondents are willing to pay \$4.84, \$3.86, and \$3.51 for the marginal improvements in the restoration of disrupted power services within 4–6 days, 1 week and 2 weeks, respectively. Notably, the WTP for the status quo option is negative. A negative WTP represents the additional amount of income that individuals would require to accept the current situation scenario.[10]

However, the marginal WTP estimates do not provide comprehensive welfare measures (compensating surplus). To estimate the overall annual WTP for a greater resilient power infrastructure (i.e., total annual WTP for a change from the status quo scenario), further computations are required. To demonstrate this process, four hypothetical resilience power infrastructure scenarios and a current situation scenario are presented. Each hypothetical resilience scenario depicts varying restoration times with regard to the current situation scenario. The current situation scenario assumes that the power services are provided to 10% of the customers within 1–3 days, 20% within 4–6 days, 50% within 1 week, and 70% within 2 weeks following a severe hurricane like Hurricane Irma.[11] The resilience scenarios are organized in a progressively faster restoration of power supply.[12]

Using Eq. (5), we estimated the compensating surplus (CS) for the change from the current situation scenario to each resilience scenario. The CS was calculated for all four scenarios, with the inclusion of the SQASC effect. The existing literature provides no clear consensus on whether SQASC effects are essential elements of welfare; in this case their inclusion greatly increases welfare measures (Meyerhoff et al. 2021). The estimates of welfare measures for the four scenarios are reported in Table 6. Among the four scenarios, scenario 4 exhibits the highest CS of \$604.70 per individual per year, followed by scenario 3 with \$559.80, scenario 2 with \$542.30, and scenario 1 with \$525.51. These results suggest a progressive increase in the CS measure for each resilience scenario compared to the base scenario.

By aggregating the per respondent CS measures, we can estimate the welfare measures for the Florida population associated with the four scenarios aimed at enhancing power infrastructure resilience in the state. The aggregate values are based on the number of households (see Table 6).[13] The Scenario 4 stands out with the largest welfare

[10] Although the survey was administered 2–3 years after a major hurricane, the estimated WTP values may be higher than they would be if more time had passed since the last hurricane.

[11] Our SQ scenario aligns with reality in highly affected areas by Hurricane Irma. For instance, the paper published by Mitsova et al. (2018) shows that the power restored in Collier County (i.e., one of the highly affected counties by Hurricane Irma) within the first 3 days are less than 10%. We designed our SQ scenario and improvement scenarios accordingly.

[12] The assessment of compensating surplus for various improvement scenarios involves examining the changes in their attribute levels relative to the status quo scenario.

[13] According to the Bureau of Economic and Business Research at the University of Florida, there are 8,676,264 households in Florida (by April 1, 2021). For more information, see: https://www.bebr.ufl.edu/wp-content/uploads/2022/02/households_2021.pdf

Table 5 Marginal willingness to pay (WTP) estimates

	Mixed logit
Factor	WTP
Improvement in power service restored within 1–3 days after a hurricane	5.5418 (4.2548–6.8287)
Improvement in power service restored within 4–6 days after a hurricane	4.8433 (2.3416–7.3449)
Improvement in power service restored within 1 week after a hurricane	3.8636 (1.5026–6.2245)
Improvement in power service restored within 2 weeks after a hurricane	3.5101 (1.4678–5.5524)
SQASC	−425.2031 (−645.3026–205.1035)

95% confidence intervals, reported in parentheses, were calculated using the delta method

estimate, totaling \$5.246 billion dollars, with scenario 3 following at \$4.857, scenario 2 at \$4.705, and scenario 1 at \$4.559 billion dollars. These welfare estimates provide valuable insights for policymakers, as they can be used to assess the potential positive outcomes of different resilience improvement policies for the community.

The power infrastructure in the State of Florida has revealed significant vulnerabilities following Hurricane Irma and it is projected that these vulnerabilities will be further exacerbated by future hurricanes. To address these issues, various initiatives and policies are currently underway to enhance the resilience of power systems in Florida. Nevertheless, it is crucial to explore alternative funding mechanisms, such as taxes, surcharges, fees etc. to implement and sustain these initiatives effectively, and ensure that customers are willing to contribute financially towards these resilience-focused policies. The findings provide evidence that customers revealed a significant level of WTP for funding the resilience programs in electricity infrastructure in Florida.

Discussion and Conclusion

In recent years, infrastructures in Florida that provide public utility services have encountered an unprecedented threat due to the intensification of hurricanes. These destructive extreme weather events have posed significant challenges to the resilience of the region's electricity infrastructure. To address these challenges, substantial projects and funding efforts have been undertaken to enhance the resilience of the electricity systems, specifically focusing on expediting the restoration of disrupted utilities. Nonetheless, it is essential to gain empirical insights into the impact and implementation of infrastructure resilience programs from the perspectives of residents. By understanding their preferences, decision-makers can refine

Table 6 Annual welfare estimates for improvement in the power infrastructure resilience using different improvement scenarios

Factor	Base scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Improvement in the power services restored within 1–3 days after a strong hurricane	10%	20%	30%	50%	50%
Improvement in the power services restored within 4–6 days after a strong hurricane	20%	40%	50%	50%	60%
Improvement in the power services restored within 1 week after a strong hurricane	50%	60%	60%	70%	70%
Improvement in the power services restored within 2 weeks after a strong hurricane	70%	90%	90%	90%	100%
Welfare Estimate: PML model (per respondent in $)	NA	525.5197 (290.6215,760.4179)	542.3017 (309.2143,775.3891)	559.8072 (326.5538,793.0606)	604.7054 (364.8099,844.601)
Welfare Estimate: PML model (across Florida population in billion $)	NA	4.559 (2.522,6.598)	4.705 (2.683,6.727)	4.857 (2.833,6.881)	5.246 (3.165,7.328)

95% confidence intervals, reported in parentheses, were calculated using the delta method their approach, leading to more effective and community-centered strategies. This, in turn, fosters stronger community-based decision-making practices for building resilience (Taeby and Zhang 2019).

In this study, a DCE was conducted on 1138 respondents in Florida, to derive the customers' WTP for the PRF. In the DCE, each respondent was faced two choice sets containing two hypothetical scenarios of improved resilience of electricity systems in terms of the percentage of customers regaining power service within specific time frames (i.e., 1–3 days, 4–6 days, 1 week, and 2 weeks) following a major hurricane event.

Three PML models were estimated, accounting for observed and unobserved preference heterogeneity. We found a clear preference among respondents for faster power restoration and a substantial WTP for funding this type of resilience program in Florida. Factors such as income, gender, age, and political affiliation influenced respondents' preferences. For example, respondents with higher income were more likely to pay a higher amount for improving power system resilience, while female respondents were less likely to participate in this program. Younger respondents and liberals demonstrated greater support for restoration policy. However, there was no statistically significant difference in terms of supporting the program between individuals who experienced at least one day of power outage (due to Hurricane Irma) and those who did not.

Our findings are consistent with the limited existing literature analyzing public preferences to assess the economic viability of enhancing the critical infrastructure resilience in response to natural disasters (Wang et al. 2018; Baik et al. 2020). Our findings demonstrate that the annual welfare gain per individual for four restoration scenarios falls within the range of \$525.51 to \$604.70, which aligns with the results reported by Wang et al. (2018). In their study, the observed welfare estimate per household per year ranged from \$75 to \$450 for improving the resilience of New York City's transportation system. By building on prior research, our study further strengthens the understanding of public preferences and economically feasible investment levels for enhancing the resilience of critical infrastructure systems. Such insights can inform policymakers and stakeholders in making informed decisions to allocate resources effectively and prioritize resilience initiatives for mitigating the impacts of natural disasters.

A comprehensive benefit-cost analysis is beyond the scope of the current study, but we can offer a rough comparison using available cost estimates. Florida Power and Light, the largest power utility in the state, recently undertook a project for installing underground power lines at a cost of \$633,000 per mile (Dunkelberger 2019). When extrapolated, this value implies that it would cost \$30 billion to bury all power lines in the State of Florida (Dunkelberger 2019). Our findings indicate total annual welfare gains of \$4.5 to \$5.2 billion from building a more resilient electric system. The present value of these benefits over a 10-year period, using an annual discount rate of 2%, falls in the range of \$40.4 to \$46.7 billion. Thus, although costs and welfare gains will vary across different types of projects, these calculations suggest that enhancing the resiliency of Florida's electric system would be welfare improving.

The results of our study have important policy implications. First, decision-makers should pay attention to household preferences regarding critical infrastructure resilience programs. Incorporating household perspectives can contribute to more efficient decision-making processes for crafting resilience strategies. By actively involving households into the planning and execution of resilience initiatives, decision-makers can enhance the effectiveness of these strategies within the community. Second, our findings highlight the importance of addressing income inequality when implementing resilience plans. The higher WTP of high-income respondents for funding resilience programs in electricity infrastructures suggests that income disparities can significantly impact the feasibility and success of such initiatives. It is therefore crucial to pay attention to vulnerable social groups (e.g., low-income households) and implementing measures such as discounts or other types of financial support to ensure their inclusion and participation in proposed resilience plans. By addressing income disparities and providing support to those in need, policymakers can foster a more equitable and effective implementation of infrastructure resilience plans.

Appendix

Enhancing Resiliency of Power Infrastructure in Florida

Hurricane Irma was one of the most destructive and the costliest hurricanes in U.S. history. It struck Florida on September 10, 2017 as Category 4 hurricane and led to millions of residents experiencing electricity outage and water supply disruption in the state during and after the hurricane. In this regard, suppose that the State of Florida is proposing to establish 'Florida Power Resiliency Fund' (FL-PRF), which will mobilize resources statewide to improve resiliency of electricity infrastructures to hurricanes and other natural hazards in Florida. Using 'FL-PRF', the State Government in collaboration with local utility providers will be able to modify and upgrade the power and electricity infrastructure to minimize power outages and disruptions and reduce the recovery time for the residents. Considering this, would you be willing to support 'FL-PRF' by contributing a specific amount of money which will be added to your annual electricity bill for next 10 years (which can be flexibly distributed across billing cycles each year).

You have several options to select the type of the 'Florida Power Resiliency Fund' (FL-PRF) with varying contribution levels. Option A will ensure a moderate level of investment in power infrastructure to provide a faster restoration of electricity supply compared to the 'Current Situation'. Option B will provide even faster restoration than Option A. Remember If you choose neither Option A nor Option B, it means that you are supporting the 'Current Situation' (Opt Out Option).

Please select the option that you prefer most for each of the two sets of scenarios presented (see Fig. 1).

Table 7 Parameter estimates for improving the power infrastructure resilience using latent class logit models

	Model 1[a]		Model 2 (Class membership)	
	Class 1	Class 2	Class 1	Class 2
Class Share	0.275	0.725	0.228	0.772
Improvement in power service restored within 1–3 days after a hurricane	0.0820*** (0.0244)	0.0424*** (0.0132)	0.1671** (0.0740)	0.0399*** (0.0125)
Improvement in power service restored within 4–6 days after a hurricane	0.0783*** (0.0254)	0.0414** (0.0179)	0.1313** (0.0579)	0.0373** (0.0155)
Improvement in power service restored within 1 week after a hurricane	0.0574* (0.0296)	0.0368*** (0.0114)	0.0945 (0.0598)	0.0362*** (0.0113)
Improvement in power service restored within 2 weeks after a hurricane	0.0946*** (0.0217)	0.0228** (0.0108)	0.1407*** (0.0415)	0.0243** (0.0105)
Status quo (current situation) option	1.8307*** (0.4437)	−12.8233 (254.0043)	1.6542* (0.8829)	−2.6255*** (0.3407)
Payment	−0.0173*** (0.0052)	−0.0055* (0.00316)	−0.0442** (0.0194)	−0.0045 (0.0029)
Assignment to Class 1				
Income			−0.0001*** (0.00003)	
age			0.0295*** (0.0057)	
African American			0.0045 (0.4887)	
White			0.3128 (0.3630)	
Other races			0.8261 (0.5094)	
Liberal			−0.6899*** (0.2493)	
Conservative			−0.1329 (0.2038)	

Table 7 (continued)

	Model 1[a]		Model 2 (Class membership)	
	Class 1	Class 2	Class 1	Class 2
Constant term	−0.9665*** (0.0774)		−2.2973*** (0.4420)	

Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

[a]There is a convergence issue when covariates are not included

Table 8 Marginal willingness to pay (WTP) estimates

	Latent Class Logit	
	Class 1	Class 2
Factor	WTP	WTP
Improvement in power service restored within 1–3 days after a hurricane	4.7330 (2.6089–6.8571)	7.6651 (3.1749–12.1553)
Improvement in power service restored within 4–6 days after a hurricane	4.5200 (1.6017–7.4383)	7.4987 (1.2105–13.7869)
Improvement in power service restored within 1 week after a hurricane	3.3157 (0.1347–6.4968)	6.6654 (−0.2727–13.6036)
Improvement in power service restored within 2 weeks after a hurricane	5.4570 (1.9830–8.9310)	4.1294 (−0.2961–8.5549)
SQASC	105.5899 (9.6551–201.5247)	−2317.1689 (−92,301.838–87,667.5)

95% confidence intervals, reported in parentheses, were calculated using the delta method.

Table 9 Annual welfare estimates for improvement in the power infrastructure resilience using different improvement scenarios

Factor	Base scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Improvement in power service restored within 1–3 days after a hurricane	10%	20%	30%	50%	50%
Improvement in power service restored within 4–6 days after a hurricane	20%	40%	50%	50%	60%
Improvement in power service restored within 1 week after a hurricane	50%	60%	60%	70%	70%
Improvement in power service restored within 2 weeks after a hurricane	70%	90%	90%	90%	100%
Welfare Estimate: Latent Class logit model: Class 1 (the SQ effect is included)	NA	8.3533 (−42.8541,59.5609)	22.5256 (−32.4614,77.5126)	5.3724 (−82.4969,93.2418)	71.9855 (6.6792–137.2919)
Welfare Estimate: Latent Class logit model: Class 2 (the SQ effect is included)	NA	2443.447 (−87,542.98,92,429.88)	2453.444 (−87,532.71,92,439.6)	2482.134 (−87,503.82,92,468.09)	2531.76 (−87,454.95–92,518.47)

95% confidence intervals were calculated using the delta method.

Acknowledgments The authors acknowledge the support received from the National Science Foundation [Award #1832693: CRISP 2.0 Type 2: Collaborative Research: Organizing Decentralized Resilience in Critical Interdependent-infrastructure Systems and Processes (ORDER-CRISP)].

Data Availability Data will be provided upon reasonable request, contingent on adherence to Institutional Review Board (IRB) guidelines.

Declarations

Competing Interests None.

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