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Household Adaptations to Infrastructure System Service Interruptions

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Abstract: When critical infrastructure system services are disrupted, households typically respond by reducing, delaying, or relocating their demand (e.g., delaying laundry), or augmenting supply (e.g., using a generator). While this phenomenon is well known, there has been little systematic empirical investigation of it. Focusing on electric power and water service interruptions and using revealed and stated preference survey data from Los Angeles County, California, we develop 24 mixed logit models, one each to predict the probability an individual undertakes a specified adaptation as a function of outage duration and characteristics of the individual. The analysis aims to determine: (1) how common different household adaptations are; (2) how adaptation implementation varies with infrastructure type, outage duration, and uses of the service; (3) what household characteristics are associated with implementation of different adaptations; and (4) how adaptations tend to occur together. The percentage of individuals who report doing an adaptation varies greatly across adaptations and outage durations, from 2% to 88%. In general, adaptations that require moving out of the home are the least common of those investigated. For electric power outages, adaptations that could be done at home are less likely as the outage duration increases, while those that require going somewhere are more likely as the duration increases. For water outages, all adaptations (except delaying consumption) are more likely as an outage lasts longer. Using electric power or water for medical devices and/or work and business has a large effect on the likelihood of implementing many adaptations. Preevent conservation habits are also associated with an increased likelihood of implementing adaptations. The influence of household characteristics varies greatly across adaptations. There is evidence that some adaptations tend to occur together (e.g., using water from lakes and the government) and others tend not to (e.g., delaying electricity use and going to a hotel). **DOI: 10.1061/(ASCE)IS.1943-555X.0000715.** *© 2022 American Society of Civil Engineers.*

Practical Applications: Knowing what kinds of adaptations are found among different segments of the population, how common they are, and when they are likely to be implemented can help policymakers know what sorts of crisis-coping behaviors to expect in their locality, and can help them to know the timeframe in which those adaptations would be implemented. This in turn can provide needed knowledge for how to support those adaptations. Such support could take the form of enhanced contacts and outreach in specific populations (e.g., medically fragile), advance planning (having materials on hand, or including adaptations in drills or exercises), or timely improvising as an event unfolds.

Introduction

When an infrastructure system service is disrupted, service users adapt in response. They find innumerable ways to modify their demand and/or augment supply to minimize the impact of the disruption. When the power goes out, for example, people may reduce demand by going to sleep early instead of working on their computer, relocate their demand by going to a friend's house and using their electricity, or augment the supply by using an outdoor gas grill to cook, a candle for light, or a generator for multiple electricity needs. This phenomenon has been observed for all types of infrastructure systems (e.g., water supply, telecommunications) and events (e.g., hurricane, ice storms) (Chakalian et al. 2018; Moreno and Shaw 2019; Scanlon 1999; Heidenstrøm and Throne-Holst 2020). In fact, these adaptations provide a critical, albeit distributed and typically uncoordinated response to service outages, substantially helping to ensure that needs are met even when the network is not functioning normally. Although an average person cannot survive without drinking water for more than a few days, for example, many water supply networks have experienced outages longer than that without mass deaths because people were able to use adaptations to meet the need. Nevertheless, despite increasing recognition of the importance of adaptations, there has been little quantitative investigation of them.

Improved understanding of how widespread different types of adaptations are; how their implementation depends on the characteristics of the service users, event, and location; and how they vary over the course of an event can be useful in at least two main ways. First, adaptations are an important mediator between *system functioning* and *household functioning*, where the former is the service provided from the pipes or power lines and the latter is the ability

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of households to participate in work, school, and leisure activities, and to drink, bathe, and live their daily lives. Civil infrastructure systems are critical precisely because of their role in household functioning, so understanding that relationship—and the adaptations in the middle of it—is important. Ultimately, systems should be managed and operated to meet goals defined in terms of household functioning. Second, on a practical level, better quantitative information about the implementation and effectiveness of various adaptations will allow system operators, emergency managers, and community organizations to better account for them in planning for response and restoration activities. They can develop efforts to facilitate effective adaptations, such as planning for charging stations during power outages, and discourage adaptations with potentially negative consequences, such as running gas stoves indoors for heat.

We define adaptations as *actions taken by the users of an infrastructure service to fulfill their needs with other methods when that service is suspended.* Focusing on electric power and water service interruptions and using revealed preference (RP) and stated preference (SP) survey-based data from Los Angeles County, we develop mixed logit models, one each to predict the probability an individual undertakes a specified adaptation as a function of outage duration and characteristics of the individual. We believe this is the first such quantitative modeling of household adaptation implementation following infrastructure service disruptions. Using this quantitative analysis, we examine the following research questions:

1. How common are different types of household adaptations?
2. How does household adaptation implementation vary with (a) infrastructure type, (b) outage duration, and (c) uses of the service?
3. What household characteristics are associated with implementation of different household adaptations?
4. Which household adaptations tend to occur together? Which tend not to?

Following a brief review of the literature on adaptations in response to service interruptions, we describe the data and mixed logit model. Subsequently, the four research questions are addressed in turn. The paper concludes with a discussion of the implications of the findings and avenues for possible future work.

Background

A small but growing literature focuses on how people adapt to interruptions in critical services such as electricity and water. Disruptions can emerge from hazard-induced damages to infrastructure systems, or from deliberate shutdowns intended to avoid triggering other hazards or to prevent system overload and damage. Here we focus on household adaptations to electric power and water service interruptions in particular. The literature in this area addresses multiple hazards and locations, including winter storms in the United Kingdom (Abi Ghanem et al. 2016) and Norway and Sweden (Heidenstrom and Kvarnlof 2017; Palm 2009), hurricanes in Florida, USA (Chaklian et al. 2018), an earthquake in Chile (Moreno and Shaw 2019); and more chronic disruptions in China (Wang and Zhang 2015), Indonesia (Aliloedin 2014), Mexico City (Eakin et al. 2016), and Sweden (Wamsler and Brink 2014). All studies we found used qualitative methods, including interviews, focus groups, and/or direct observations. Together they provide a rich depiction of household experiences. Moreno and Shaw (2019), for example, highlight the use of local knowledge in adapting to water outages by finding hidden streams used in the past. Abi Ghanem et al. (2016) discuss the importance to adaptations of helping between friends, neighbors, and community members. The literature also collectively offers over 50 examples of different adaptations to losses of electricity and water, implemented by individuals and groups. The menu of possible adaptations ranges as far as people's creativity and available resources. In the research described herein, we use that list of previously observed adaptations to identify a sample for further study (listed in Table 1). We add to the mostly qualitative literature by, for the first time, developing a large survey-based data set that includes both RP and SP data, and using it to develop statistical models of adaptation implementation. This different methodological approach facilitates investigation of the four research questions posed.

Data

Survey Overview

We deployed a web-based survey in May–December 2020. The survey, which was designed to capture individuals' responses to electric power and waters supply service outages, included sections on (1) typical electric power and water use patterns; (2) past experiences with electric power and water supply outages; (3) expected responses to hypothetical electric power and water outages of varying durations; (4) risk perception, emergency preparedness, and social capital; and (5) demographics.

The quota-based survey sample was obtained through Qualtrics and included only individuals at least 18 years old living in Los Angeles County. Participants were recruited from multiple Qualtrics panels, using travel points and other incentives, until the appropriate census-representative sample was achieved based on age, gender, race, education, and income, characteristics usually found to be important in studies of risk, preparedness, vulnerability, and resilience (e.g., Martins et al. 2018, 2019; Bourque et al. 2013). Several data quality checks were implemented, including omitting responses that were located outside Los Angeles; were completed in an unrealistically short time (<8.0 min), indicating lack of consideration; were gibberish; or appeared to be the result of straightlining (i.e., rushing through a survey clicking on the same response for every question). Excluding these responses was intended to improve data quality by omitting respondents who were just doing it to collect the incentive but not providing thoughtful answers. Unlike a paper survey where one can keep the incentive without completing the survey, in this case the survey had to be completed to get the incentive. A total of 3,129 responses were initiated, and after applying the quality checks and filters, the final sample included 1,615 observations for use in the analysis, for a completion rate of 51.9%. Respondents completed the survey in an average of 23.5 min. All elements of the study design and instrumentation were reviewed and approved by our university Institutional Review Board. By using Qualtrics to deploy the survey during the COVID-19 pandemic, we ensured people would not be nervous about touching their mail, and we avoided postal delays, which would affect completion and response rates.

Adaptation Adoption and Outage Duration Variables

The survey elicited both RP and SP data for the binary response variable, y, *do adaptation* (1) or *do not do adaptation* (0). Whereas RP data relate to actual past choices in real-world situations, SP data describe intentions in hypothetical future situations. RP data reflect actual choices and thus have high reliability and face validity, but they are not available for situations that the respondent has not experienced, in this case longer duration outages (Train 2009). Questions to elicit SP data can be designed to address new or hypothetical choices and to contain more attribute variation,

Table 1. Number of SP responses for each adaptation by infrastructure type

Variable	Adaptation	Electric power				Water supply			
		1 day	3 days	1 week	1 month	1 day	3 days	1 week	1 month
y_{gen}	Used my generator[a]	580	634	741	808	N/A	N/A	N/A	N/A
y_{candle}	Used candles, flashlight, and/or lantern[b]	1,417	1,302	1,124	975	N/A	N/A	N/A	N/A
y_{heater}	Used a nonelectric heater and/or fireplace[c]	666	671	713	670	N/A	N/A	N/A	N/A
y_{stove}	Used a gas stove and/or camping stove to cook meals and/or boil water[b,c]	1,044	1,070	1,055	1,007	N/A	N/A	N/A	N/A
y_{car}	Charged cell phone in the car[d]	1,205	1,231	1,167	1,101	N/A	N/A	N/A	N/A
y_{shop}	Charged cell phone, laptop, and/or tablet at work and/or in a coffee shop[c]	900	1,015	1,051	1,040	N/A	N/A	N/A	N/A
y_{center}	Went to a cooling or warming center[e]	471	526	647	734	N/A	N/A	N/A	N/A
y_{lake}	Used water from lakes, rivers, and/or creeks[e]	N/A	N/A	N/A	N/A	414	429	480	592
y_{govt}	Used water delivered by the government[f]	N/A	N/A	N/A	N/A	950	1,033	1,185	1,235
y_{tank}	Used water from private tank and/or rain barrel[g]	N/A	N/A	N/A	N/A	633	669	726	742
y_{tub}	Used water stored in the bathtub and/or pool[h]	N/A	N/A	N/A	N/A	568	611	631	666
y_{bottle}	Purchased bottled water[f]	N/A	N/A	N/A	N/A	1,199	1,278	1,315	1,293
y_{reduce}	Reduced consumption of electricity [water] (e.g., cooked less)[i]	1,238	1,220	1,207	1,187	1,125	1,154	1,132	1,113
y_{delay}	Delayed consumption of electricity [water] (e.g., postponed doing laundry)[b,c]	1,114	1,088	1,044	1,014	932	860	775	777
y_{visit}	Visited a relative's or friend's house for their heat or AC [water and/or laundry facilities][j]	550	662	798	877	647	741	987	1,047
y_{move}	Moved to a relative's or friend's house[j]	416	504	738	904	444	544	800	917
y_{hotel}	Moved to a hotel[a]	316	447	702	825	324	468	708	879
y_{town}	Moved out of town[a]	256	262	360	594	300	326	431	632
y_{other}	Other	237	271	294	330	251	278	300	336
	Average	744	779	832	862	649	699	789	852

[a]Chakalian et al. (2018).
[b]Heidenstrøm and Kvarnlöf (2017).
[c]Abi Ghanem et al. (2016).
[d]Teel, n.d.
[e]Moreno and Shaw (2019).
[f]Eakin et al. (2016).
[g]Aliloedin (2014).
[h]Palm (2009).
[i]Wang and Zhang (2015).
[j]Wamsler and Brink (2014).

but may be subject to bias if what people say they will do differs from what they actually will do (Louviere et al. 2000; Lavasani et al. 2017). Combining the two data types allows us to leverage the strengths of each. The coefficients that represent the relative importance of explanatory variables are estimated using both types of data, reflecting the amount of variation each type includes. The alternative-specific constants (ASCs), which represent the average probability of doing an adaptation, are estimated separately for RP and SP data. By using the RP ASCs, we avoid the bias associated with the SP data.

Six questions were asked to solicit information associated with a past outage (RP data), three for electric power and three for water supply. The questions and {*answer choices*} were as follows. **Q1**. Have you ever experienced an electricity outage [disruption in water service] at your place of residence? {*Yes*, *No*}. **Q2**. Approximately how long did the electricity outage [water disruption] last? (If you have experienced more than one outage, please select the length of the longest outage that you can remember.) {*Less than one hour*, *1 hour*, *12 hours*, *1 day*, *3 days*, *1 week*, *1 month*}. **Q3**. Which of the following did you do, if any, to meet your household electricity [water] needs during the longest outage that you experienced? (Select all that apply) {*list of adaptations*}. For electricity and water, respectively, the 13 and 11 adaptations applicable to the infrastructure type in Table 1 were listed.

Similarly, two questions were asked to solicit information associated with hypothetical future outages (SP data), one for electric power and one for water supply. The question and {*answer choices*} were **Q4**. For each expected duration of the outage, which of the following actions would you do to meet your household electricity [water] needs? For each of the 13 [11] adaptations listed in Table 1, and for each of four outage durations—1 day, 3 days, 1 week, and 1 month, there were two options {*Yes*, *No*}. The specific adaptations were selected to represent a range of types identified in past events or literature.

Tables 1 and 2 summarize the number of respondents who indicated they would do each adaptation by outage duration, for SP and RP questions, respectively. Across all adaptations, an average of 2.7%, 1.3%, 0.3%, and 0.3% of responses are RP for 1 day, 3 days, 1 week, and 1 month, respectively. This illustrates the value of including hypothetical future outage data to provide a larger range of durations than past outages would alone.

Other Explanatory Variables

The explanatory variables, which vary with the individual respondent and were selected based on the literature (Moreno and Shaw 2019; Dargin and Mostafavi 2020; Heidenstrom and Throne-Holst 2020; Klinger et al. 2014; FEMA 2013; Martins et al. 2018; Clay et al. 2020), include those related to (1) how the service (electric power or water) is used ($x_{\text{e.use}}$, $x_{\text{w.use}}$, $x_{\text{e.source}}$, $x_{\text{w.source}}$, $x_{\text{e.con}}$, $x_{\text{w.con}}$), (2) risk perception and past experience in emergencies

Table 2. Number of RP responses for each adaptation by infrastructure type

Variable	Adaptation	Electric power							Water supply						
		<1 h	1 h	12 h	1 day	3 days	1 week	1 month	<1 h	1 h	12 h	1 day	3 days	1 week	1 month
y_{gen}	Used my generator[a]	19	41	22	22	8	3	3	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{candle}	Used candles, flashlight, and/or lantern[b]	165	420	235	97	38	12	8	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{heater}	Used a nonelectric heater and/or fireplace[c]	4	18	18	11	7	4	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{stove}	Used a gas stove and/or camping stove to cook meals and/or boil water[b,c]	16	55	58	37	22	6	1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{car}	Charged cell phone in the car[d]	41	99	104	50	22	6	4	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{shop}	Charged cell phone, laptop, and/or tablet at work and/or in a coffee shop[c]	15	54	60	29	12	5	4	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{center}	Went to a cooling or warming center[e]	3	6	13	2	4	0	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
y_{lake}	Used water from lakes, rivers, and/or creeks[e]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2	4	4	3	1	0	1
y_{govt}	Used water delivered by the government[f]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3	17	8	2	2	0	3
y_{tank}	Used water from private tank and/or rain barrel[g]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	6	17	14	8	7	0	3
y_{tub}	Used water stored in the bathtub and/or pool[h]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	9	33	23	13	9	0	1
y_{bottle}	Purchased bottled water[f]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	33	105	77	39	21	4	5
y_{reduce}	Reduced consumption of electricity [water] (e.g., cooked less)[i]	23	59	65	24	7	3	2	14	61	55	25	11	1	2
y_{delay}	Delayed consumption of electricity [water] (e.g., postponed doing laundry)[b,c]	48	154	117	47	17	3	2	27	123	80	32	16	3	4
y_{visit}	Visited a relative's or friend's house for their heat or AC [water and/or laundry facilities][j]	4	26	20	13	3	1	1	8	17	19	16	7	2	4
y_{move}	Moved to a relative's or friend's house[j]	7	10	19	6	7	1	4	5	14	9	15	4	0	1
y_{hotel}	Moved to a hotel[a]	3	13	9	8	9	5	2	5	11	10	10	9	1	1
y_{town}	Moved out of town[a]	3	0	5	3	2	0	3	2	7	2	0	2	0	1
y_{other}	Other	12	7	16	1	0	0	0	3	4	2	1	0	0	0
	Average	26	69	54	25	11	4	3	10	34	25	14	7	1	2

[a]Chakalian et al. (2018).
[b]Heidenstrøm and Kvarnlöf (2017).
[c]Abi Ghanem et al. (2016).
[d]Teel, n.d.
[e]Moreno and Shaw (2019).
[f]Eakin et al. (2016).
[g]Aliloedin (2014).
[h]Palm (2009).
[i]Wang and Zhang (2015).
[j]Wamsler and Brink (2014).

($x_{l.emer}$, $x_{w.emer}$, $x_{n.emer}$, x_{prep}), (3) social capital (x_{neigh}, x_{rel}), and (4) sociodemographics (all other variables). Tables 3 and 4 summarize the descriptive statistics for the categorical and continuous variables, respectively.

To obtain data for the five variables related to use of the service, respondents were asked "In what ways does your household regularly use electricity [water] at your place of residence? (Select all that apply.)" Of the 10 choices for electricity—house heating, house cooling, lighting, cooking and food storage, communications, electronics, washing, medical devices, work and business, or other—only options for medical devices and work/business were included ($x_{e.use}$), as they were hypothesized to be most important as possible predictors of adaptation. Of the 10 choices for water—drinking, bathing, cooking, washing, flushing the toilet, medical devices, work and business, swimming pool or hot tub, outdoor uses (lawn, garden), and other, options were included only for medical devices, work/business, and pool/hot tub ($x_{w.use}$). To determine whether someone might have a backup source of electric power or water, we asked "Which of the following energy [water] sources does your household use at your place of residence? (Select all that apply)" and coded responses as one source or multiple sources. Finally, we asked "In the past five years, to what extent have you taken actions to conserve electricity at your place of residence (examples: turning lights/appliances off when not in use, use LED lamps, limit the use of appliances)?" The four choices (not at all, to a minor extent, to a moderate extent, to a major extent) were coded as binary. The same question was asked for water but with the following examples: taking fewer showers, installing high efficiency toilets/plumbing fixtures, purchasing high efficiency washers.

Respondents were asked several questions to elicit information about their risk perception and past experience in emergencies. The question "How likely do you think it is that you and your household will be impacted by emergencies in the next five years?" included five options (very unlikely, unlikely, likely, very likely, not sure), but was coded as a binary variable ($x_{l.emer}$). Similarly, the question "How worried are you about the potential threat of you and your household being impacted by emergencies in the next five years?" included four options but was coded as binary ($x_{w.emer}$) (Table 3). The negative emergency variable data ($x_{n.emer}$) was obtained by asking "Have you ever experienced emergencies that caused some negative impact on your life? (yes or no)." Respondents were asked, "Emergency management agencies have suggested the following ways to prepare for emergencies in Los Angeles. For each one, please check if you have done it in order to be prepared for emergencies." Twelve possible activities were listed—preparing an evacuation plan, preparing a household reunion plan, searching for preparation information, storing important documents, keeping extra medication, keeping extra cash, gathering emergency numbers, storing three days of water per person, storing nonperishable food and snacks, storing first aid supplies, storing flashlights, and

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Table 3. Number of respondents associated with each level of categorical variables

Variable	Description	Levels[a]	Number of respondents
x_{type}	Infrastructure service type	0: Electric	1,615
		1: Water	1,615
$x_{e.use}$	Electricity uses	0: None	1,128
		1: Medical devices	77
		2: Work and business	346
		3: Both medical and work	64
$x_{e.source}$	Electricity sources	0: Single source	418
		1: Multiple sources	1,197
$x_{e.con}$	Electricity conservation	0: Not at all or to a minor extent	605
		1: To a moderate or major extent	1,010
$x_{w.use}$	Water uses	0: Neither	1,208
		1: Medical devices	42
		2: Work and business	69
		3: Swimming pool or hot tub	224
		4: Two or more of medical, work, swim	72
$x_{w.source}$	Water sources	0: Single source	824
		1: Multiple sources	791
$x_{w.con}$	Water conservation	0: Not at all or to a minor extent	783
		1: To a moderate or major extent	832
$x_{l.emer}$	Perceived likelihood of emergency in next 5 years	0: Very unlikely, unlikely, not sure	515
		1: Likely or very likely	1,100
$x_{w.emer}$	Worry about emergency in next 5 years	0: Not at all or slightly worried	885
		1: Moderately or extremely worried	730
x_{n_emer}	Has experienced a negative emergency	0: Have not had negative experience	1,134
		1: Has had a negative experience	481
x_{gen}	Gender	0: Female	838
		1: Male	769
		2: Other	8
x_{race}	Race	0: Asian	223
		1: Black	131
		2: Hispanic	802
		3: Other	31
		4: White	428
x_{edu}	Education	0: <4-year degree	1,155
		1: 4-year degree+	460
x_{child}	Children (<18 y) live in household	0: No	918
		1: Yes	697
x_{elder}	Elders (65 + y) live in household	0: No	1,176
		1: Yes	439
x_{pets}	Pets live in household	0: No	612
		1: Yes	1,003
$x_{med.c}$	Anyone with a medical condition in household	0: No	1,167
		1: Yes	448
$x_{med.e}$	Anyone in household rely on medical equipment	0: No	1,426
		1: Yes	189
x_{own}	Homeownership	0: Do not own	788
		1: Own	827
x_{house}	House type	0: Apartment	492
		1: Single-family, duplex, townhome	1,061
		2: Other	62
x_{employ}	Employment status	0: Not traditionally employed	720
		1: Employed full-time or part-time	895

Table 3. (*Continued.*)

Variable	Description	Levels[a]	Number of respondents
x_{marital}	Marital status	0: Not married	928
		1: Married	687
x_{neigh}	Feels connection to neighborhood	0: Does not feel connected	572
		1: Feels connected	1,043

[a]For the n-level categorical variables, Level 0 corresponds to $x_1 = \ldots = x_n = 0$, Level 1 corresponds to $x_1 = 1$ and $x_2 = \ldots x_n = 0$, Level 2 corresponds to $x_2 = 1$ and $x_1 = x_3 = \ldots = x_n = 0$, etc.

Table 4. Descriptive statistics for continuous variables

Variable	Description (unit)	Number of responses	Mean	Standard deviation
$x_{\text{e.dur}}$	Outage duration, electricity (h)	1,302	18.88	81.29
$x_{\text{w.dur}}$	Outage duration, water (h)	522	25.41	99.61
x_{prep}	Preparation[a]	1,615	7.01	3.38
x_{age}	Age (years)	1,611	41.96	16.40
x_{inc}	Income[b] ($1,000s)	1,615	77.47	65.33
$x_{\text{yr,h}}$	Time living at current address (years)	1,590	14.20	12.50
$x_{\text{yr},c}$	Time living in Los Angeles County (years)	1,600	31.12	17.78
x_{rel}	Number of people to rely on for assistance	1,615	2.28	1.36

[a]Preparation is a continuous value from 0 to 12.
[b]Income was asked as an interval variable but was coded as a continuous variable with the values in parentheses for each interval: less than $15k ($7.5k), $15k–$35k ($25k), $35k–$50k ($42.5k), $50k–$75k ($62.5k), $75k–$100k ($87.5k), $100k–$150k ($125k), $150k–$250k ($200k), and more than $250k ($300k).

storing a battery-operated radio. The preparation (x_{prep}) variable was then coded as the number of preparation-based activities respondents took out of 12.

To examine the possible role of social capital on adaptation adoption, respondents were asked, "Thinking about your neighborhood, how much do you agree or disagree with each of the following sentences: (1) People in this neighborhood are willing to help neighbors (Sampson et al. 1997), (2) People in this neighborhood know each other well, (3) People in this neighborhood can be trusted (Sampson et al. 1997), (4) People in this neighborhood participate in neighborhood organizations, and (5) My neighborhood is a safe place" (Merrin et al. 2015). The choices were strongly disagree, disagree, agree, and strongly agree. To create the composite neighbor connectedness variable, values of 1–4 were assigned to each response choice, respectively, answers for the five statements were averaged, and x_{neigh} was coded as 0 for *does not feel connected* (≤2.5), and 1 for *feels connected* (>2.5). The reliable people variable, x_{rel}, was based on the question "How many close friends, relatives, or neighbors do you have nearby to rely on for assistance during an emergency?"

Respondents were asked to list how many children (<18 years), elders (65+ years), and pets lived in their household, and those responses were coded as binary variables, x_{child}, x_{elder}, and x_{pets}. Employment status (x_{employ}) was treated as binary with *unemployed*, *student*, *homemaker*, *retired*, and *unable to work* combined into *not traditionally employed*. Two questions were asked to capture possible medical reliance on infrastructure services. The first was "Do you have any people in your household who have at least one of the following conditions? (Select all that apply)," with six choices—seriously impaired hearing; seriously impaired vision; serious difficulty concentrating, remembering, or making decisions; serious difficulty walking/climbing stairs; serious difficulty dressing or bathing; and serious difficulty doing errands alone. The second was "Do you have any people living regularly in your household who rely on medical equipment in the home (such as, but not limited to, respirators, ventilators, suction, home dialysis, etc.)?" Both $x_{\text{med.c}}$ and $x_{\text{med.e}}$ were coded as binary.

Mixed Logit Model

This study focuses on individuals' adaptation decisions. As a choice between two alternatives—do specified adaptation k or not—it lends itself to representation as a discrete choice model. In particular, we developed mixed logit models (also known as random parameter logit models) because they are able to capture that the data (1) is panel data; and (2) includes both RP and SP data. First, each respondent answered up to five questions for one single infrastructure system and adaptation, one for a past outage and four for hypothetical future outages of different durations (1 day, 3 days, 1 week, 1 month). That is, there are five well-ordered choice situations, t, and as a result, there may be some correlation among responses of a single individual across multiple questions. Second, the data set includes both RP and SP data. As the choice situations for RP and SP differ, the variance of the unobserved factors may differ in the two situations as well. Thus, we should allow the scale for the RP responses to differ from the scale for the SP responses. In addition, the actual RP choices may influence SP choices, the concept of state dependence (Bhat and Castelar 2002). In this case, someone who has done an adaptation in the past may be more or less likely to say they intend to do it in the future as well.

We develop a separate model for each specific adaptation-infrastructure type k (e.g., use a generator for an electric power outage). For each of these 24 models, we adopted the Bhat and Castelar (2002) unified framework, without inclusion of interalternative error structure (i.e., with $\mu = 0$), which does not apply because there are only two alternatives. In each choice situation t, each individual i is assumed to choose the alternative j that maximizes their utility, U_{ijt}, defined as

$$U_{ijt} = \alpha_j + \tau_{\text{dur}} x_{\text{dur},t} + \vec{\gamma}^T \vec{x}_i + \varphi_i[(1 - \kappa_{RP,it}) Y_{ij}] + \varepsilon_{ijt} \quad (1)$$

The α_j is the ASC for alternative j. The variable $x_{\text{dur},t}$ is the outage duration for choice situation t and $\vec{x}_i$ is a vector of observed covariates relating to the individual-specific variables for individual i. The coefficients τ_{dur} and $\vec{\gamma}$ are the corresponding coefficients for outage duration and the individual-specific variables. For the ASC, duration, and individual-specific variables, only differences between alternatives are relevant, not their absolute values, so with $J = 2$ alternatives, one at most can enter the model. For these, therefore, we normalize the values for j = *do not do adaptation* to zero. The value of the ASC can be considered the average effect of all factors not in the model on the utility of doing the adaptation relative to not doing the adaptation. Similarly, the values of $\vec{\gamma}$ can be considered the effect of each associated $\vec{x}_i$ variable on the utility of doing the adaptation relative to not doing the adaptation.

The individual-specific state-dependence effect, φ_i, represents the effect of the RP choice on the utility of the SP choice situation; $\kappa_{RP,it}$ is a dummy variable that is one if choice situation t for individual i corresponds to an RP choice and zero otherwise; and Y_{ij} is a binary value that is one if individual i experienced an outage in the past and adopted alternative j during the past outage and zero otherwise. For each RP choice situation, because $\kappa_{RP,it} = 1$, the entire fourth term in Eq. (1) reduces to zero. Thus, the term as a whole has the effect of adding φ_i to the utility equation for alternative j in each SP choice situation if individual i chose j in the RP choice situation; it has no effect on any other utilities. Finally, ε_{ijt}, an unobserved random term that captures omitted variables, is assumed to be independently and identically extreme value I distributed across alternatives and individuals for each choice situation, and independently (but not identically) distributed across choice situations (Bhat and Castelar 2002).

To accommodate potentially different SP and RP scales, we normalize the scale parameter for the RP data to one and define the scale parameter for the SP data relative to that of the RP data (Train 2009; Hensher et al. 2008). The scale parameter for individual i in choice situation t, λ_{it}, is

$$\lambda_{it} = [(1 - \kappa_{RP,it})\lambda] + \kappa_{RP,it} \tag{2}$$

where λ = SP scale relative to RP. We estimated λ as described in Hensher et al. (2008) by including an ASC into the SP data that has a zero mean and free variance. According to the extreme value Type I distribution then, $\lambda = \pi/(\sigma\sqrt{6})$, where σ is the estimated standard deviation of the ASC of the SP choice (Train 2009; Hensher et al. 2008). Thus, the ASC estimated using the SP data was not available, and we used the ASC estimated with the RP data, which we expect is more reliable anyway. The modeling was implemented using the {gmnl} package in R (R Core Team 2021; Sarrias and Daziano 2017).

If, for simplicity of notation, we define $\vec{\boldsymbol{\beta}}_i = (\alpha_j, \tau_{\text{dur}}, \vec{\boldsymbol{\gamma}}, \varphi_i)^T$ and $\vec{\boldsymbol{w}}_{ijt} = (1, x_{\text{dur},t}, \vec{x}_i, [(1 - \boldsymbol{\kappa}_{RP,it})Y_{ij}])^T$, then $U_{ijt} = \vec{\boldsymbol{\beta}}_i^T \vec{\boldsymbol{w}}_{ijt} + \varepsilon_{ijt}$. The coefficient vector $\vec{\boldsymbol{\beta}}_i$ varies across individuals. If we let the distribution of unobserved heterogeneity across individuals be a multivariate random variable $\tilde{\beta}$ with parameters $\vec{\theta}$, and $\vec{\boldsymbol{L}}_{ij}(\tilde{\beta})$ be the probability individual i makes a sequence of choices $\vec{\boldsymbol{j}} = \{j_1, \ldots, j_T\}$ over all choice situations t, conditional on $\tilde{\beta}$, then the unconditional probability that individual i chooses alternative j (*do adaptation* or *do not do adaptation*) is (Train 2009)

$$\begin{aligned} \mathrm{P}(y_i = j) &= \int \vec{\boldsymbol{L}}_{ij}(\tilde{\beta}) f(\tilde{\beta}|\vec{\boldsymbol{\theta}}) d\tilde{\beta} \\ &= \int \left(\prod_{t=1}^{T} \frac{\exp[\lambda_{it}(\beta_i^T w_{ijt})]}{\sum_n \exp[\lambda_{it}(\beta_i^T w_{ijt})]} \right) f(\tilde{\beta}|\vec{\theta}) d\tilde{\beta} \end{aligned} \tag{3}$$

Final Adaptation Implementation Models

A model was fitted for each adaptation using all the explanatory variables in Tables 3 and 4 (except infrastructure type, x_{type}), and treating ASC SP and state dependence as random parameters. Specifically, the normal distribution was used to capture the randomness of the ASC SP and state-dependence parameters, and 10 Halton draws were used for the numerical solution of the proposed mixed logit model. Recall that the ASC SP's variance is needed to estimate the scale parameter via the one-to-one relation. Tables 5 and 6 present the 13 and 11 final models for each adaptation for electric power and water supply outages, respectively. The McFadden's pseudo-R^2 values were computed as $\rho = 1 - LL(\hat{\beta})/LL(0)$, where $LL(\hat{\beta})$ and $LL(0)$ are, respectively, the log-likelihood values of the models with estimated parameters and with ASCs only (Train 2009). While the results vary by model, the pseudo-R^2 values range from 0.14 to 0.38, with an average of 0.26 and similar levels for electric power and water adaptations. These indicate reasonably good model fits. According to Louviere et al. (2000), "between 0.2 and 0.4 are considered to be indicative of extremely good model fits."

In all models, the scale of SP relative to RP, λ, is highly significant ($p < 2.2 \times 10^{-16}$), affirming the importance of allowing the scales to differ. The SP-to-RP scale was less than one in every model (0.318–0.796, with an average value of 0.476), indicating that the error variance in the SP choice context was higher than that in the RP choice context. In 16 of the 24 models, the mean state-dependence parameter, φ, is statistically significant at $\alpha = 0.05$, with those values ranging from 0.29 to 1.60 and averaging 0.71. All statistically significant state-dependence parameters are positive, indicating that on average, people who said they did an adaptation in the past were more likely to say they would in the future, and conversely, people who said they had not done an adaptation in the past were less likely to say they would in the future. The standard deviations of the state-dependence parameters were statistically significant for only three models ($p = 0.01$, 0.02, 0.04), suggesting that while it is important to include the state-dependence parameter, in the future it would be reasonable to consider it constant across individuals (i.e., let $\varphi_i = \varphi$ for all individuals i).

Because they are more easily interpreted than coefficients, the average marginal effects (AME) were computed for each explanatory variable that was statistically significant at $\alpha = 0.05$ (Tables 7 and 8). The marginal effect is defined as the change in the probability of doing adaptation k given a unit increase in the variable, keeping all other variable values constant. The marginal effects vary by observation, so we compute them for each observation, keeping all other variables at their original values and including random effects at their means, then take the average (Hensher et al. 2015). These model results are interpreted more fully in addressing Research questions 2b, 2c, and 3.

Results and Discussion

Adaptation Adoption Frequency

Although many adaptations have been observed in past events, there is little systematic information about how common they actually are. While the commonness certainly varies with event and individual, Research question 1 asks overall, *How common are different types of household adaptations?* Figs. 1(a and b) illustrate the percentage of respondents who said they did or would do each adaptation, for electric power and water, respectively. The percentages of respondents who said they did or would do each adaptation vary greatly across adaptations and outage durations, from 2% to 88%. Using candles, flashlight, and/or lantern y_{candle} is the most

Table 5. Electric power adaptation models

Variable[a]	Power generator, y_{gen}	Candles/ flashlight, y_{candle}	Heater/ fireplace, y_{heater}	Stove, y_{stove}	Car, y_{car}	Coffee shop, y_{shop}	Center, y_{center}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
ASC RP	**−2.3741***	**−1.0294***	**−3.3019***	**−3.7882***	**−3.5293***	**−3.1532***	**−3.3698***	**−4.7247***	**−2.9043***	**−2.6621***	**−2.3498***	**−2.1962***	**−2.2705***
Outage duration, x, dur	**0.0016***	−0.0026*	0	−0.0004^{3}	−0.0009*	**0.0008***	**0.0019***	−0.0004****	−0.0007x	**0.0017***	**0.0026***	**0.0024***	**0.0031***
Electricity usage 1, x, e.use1	0.309	−0.3698	−0.534	0.1432	−0.0205	−0.025	0.1691	−0.7252	0.0732	−0.0221	0.2653	**0.5289******	0.5788
Electricity usage 2, x, e.use2	−0.17	**0.5577***	0.1991	0.1677	**0.4307****	**0.672***	−0.2396	**0.6444***	**0.7404***	0.0085	0.0398	0.0435	−0.217
Electricity usage 3, x, e.use3	**0.6424******	−0.1089	**0.8889*****	0.0624	0.4007	**0.8441*****	**1.2928****	0.5276	0.2885	0.0589	**0.7284*****	**0.6937*****	**1.0293*****
Electricity sources, x, e.source	−0.0658	**0.3216*****	−0.0918	**0.4384*****	**0.3143******	0.1203	−0.0795	**0.5935****	**0.4398*****	0.0872	−0.0134	−0.0492	−0.0242
Electricity conservation, x, e.con	**0.3268******	**0.2729*****	0.1819	**0.6606***	**0.3528*****	**0.2698******	0.1963	**0.7301***	**0.498***	−0.0776	0.0134	−0.1119	**−0.3244******
Emergency likely, x, l.emer	−0.1063	**0.3093*****	0.04	0.0007	**0.2649******	0.042	−0.019	**0.4114*****	**0.382*****	0.1987	−0.1147	−0.153	−0.2614
Emergency worry, x, w.emer	0.0208	−0.0552	−0.2471	0.048	0.1041	**0.4124*****	**0.4239******	0.1555	−0.0104	0.026	0.1142	0.0835	0.0243
Emergency negative, x, n.emer	−0.0333	0.0054	−0.048	0.2622	0.1275	0.1072	0.1475	0.1015	**0.3678*****	0.0186	0.0199	0.0718	−0.0073
Preparation, x, prep	**0.0731****	0.0388^{3}	0.0567	**0.0728****	0.0292	0.0369	**0.0705*****	0.0362	0.0182	−0.0004	−0.0204	−0.0241	**0.057******
Age, x, age	**−0.0476***	0.0025	**−0.0348***	**−0.0117******	0.0103****	0.0004	−0.0137	0.0104	0.0019	**−0.0216***	**−0.0168****	**−0.0185***	**−0.0422***
Income, x, inc	−0.001	−0.0007	0.0018	−0.0014	−0.0006	0.001	−0.0026	0.0011	0.0015	0.002	**0.0022******	**0.0043***	**0.0035******
Gender 1, x, gen1	−0.0748	**−0.3659****	−0.0141	−0.1048	−0.0786	−0.163	**−0.3883******	−0.0669	−0.1063	**−0.4933***	−0.2227	−0.1855	−0.2164
Gender 2, x, gen2	−1.1983	−1.2536	0.5396	−0.6427	**−1.6554******	0.1025	0.8456	−0.8841	−0.1001	−0.7428	−0.1714	−0.9682	−0.503
Race 1, x, race1	0.5829	0.1608	0.6095	−0.314	0.4118	−0.0641	0.0635	−0.5209	**−0.5748******	−0.4093	−0.393	−0.2021	**−0.7154******
Race 2, x, race2	0.1875	**0.6358***	0.1306	−0.2128	0.2632	−0.2572	−0.2256	−0.2764	−0.2213	**−0.3363******	**−0.5629****	**−0.5811***	**−0.6317*****
Race 3, x, race3	0.4236	0.6131	−0.1444	0.2951	0.1484	0.1776	**−1.5715******	0.4121	0.2225	0.1653	**−1.0716******	−0.2597	−0.9174
Race 4, x, race4	**0.4484******	0.2346	0.2323	−0.3738	0.1415	−0.366	−0.4468	−0.2888	−0.1841	−0.1944	**−0.6107****	**−0.3645******	−0.1194
Education, x, edu	**−0.312******	**0.5265***	−0.2588	0.0981	0.2314	**0.3167******	−0.1172	0.2826	0.1539	−0.1337	−0.1189	−0.1686	−0.6771*
Child, x, child	**0.3319******	0.016	0.1265	0.2612	**0.2492******	0.2579	**0.4458******	0.0736	0.1416	**0.2833******	**0.4981***	0.0101	0.1423
Elders, x, elder	−0.19	0.0577	−0.156	−0.1566	−0.1604	−0.3115	−0.0036	0.3325	0.2613	−0.0423	−0.249	−0.1435	**−0.4224******
Pets, x, pets	−0.0027	0.1628	0.1953	0.1309	**0.3668*****	0.1935	−0.343	**0.5581****	**0.3716*****	0.0712	−0.0467	−0.0389	−0.1897
Medical condition, x, med.c	−0.1239	−0.2046	**0.6766****	0.0408	−0.0531	0.225	**0.7772****	−0.0847	−0.2642	0.229	0.0935	0.2247	**0.3934******
Medical equipment, x, med.e	0.1099	−0.1529	0.0322	−0.0303	−0.1193	**−0.5303******	0.0898	−0.2966	**−0.4097******	0.2875	**0.4311******	0.2675	**0.5966******
Home owner, x, own	**0.3776******	−0.1935	0.3062	−0.1395	0.0706	0.1285	−0.1115	0.1664	**0.4589*****	0.1823	0.0372	−0.0916	−0.1992
House type 1, x, house1	0.3217	0.0486	0.3083	**0.5038*****	0.0711	**−0.3887*****	−0.108	−0.2228	−0.1226	−0.0895	−0.2365	−0.2091	−0.3243
House type 2, x, house2	0.4089	−0.3237	**1.0029******	0.5078	−0.1434	−0.344	−0.555	−0.6922	−0.3869	−0.5298	−0.6552	−0.4511	−0.0242
Years home, x, yr.h	0.004	0.0044	−0.0108	0.0113	**−0.0108******	−0.0114	0.0018	−0.0093	0.0003	**−0.014******	−0.0046	−0.0011	0.012
Years county, x, yr.c	0.0024	**0.0099*****	−0.0039	**0.0104******	0.0046	−0.0053	**−0.0207*****	0.003	0.0039	0.003	0.0002	−0.0016	−0.0111
Employment status, x, employ	−0.0267	0.0085	0.064	0.0143	0.2185	0.2405	−0.3075	−0.0875	−0.2283	0.0684	−0.1179	0.0351	−0.0612
Marital status, x, marital	**0.54****	−0.0087	0.2449	0.2166	−0.108	−0.1037	**0.4374******	−0.0168	−0.0531	−0.2704	−0.2464	0.2249	**0.5094*****
Reliable people, x, rel	0.0998	**0.1235****	0.0901	**0.1328*****	0.0995****	**0.1658****	0.0385	**0.1433*****	0.0681	**0.2757***	**0.1699****	0.0023	0.003
Neighborhood con., x, neigh	0.0793	0.0816	0.0718	−0.1439	−0.0712	0.102	0.0937	−0.0583	0.0248	−0.0454	0.1464	0.1299	−0.1121
State dependence, φ_i, mean	**0.9361***	**0.3327***	**1.0242***	**0.6807***	**0.2898*****	**0.5834***	**0.988***	0.0884	**0.5532***	**0.4224****	**0.4047****	0.1319	**0.4255******
State dependence, φ_i, standard deviation	0.0401	0.0616	0.0501	**0.3508******	0.1347	0.0393	0.2496	0.0174	0.0101	0.0482	0.0131	0.0589	0.0797
SP scale relative to RP, λ	**0.4094***	**0.6167***	**0.3465***	**0.4159***	**0.4694***	**0.4422***	**0.4417***	**0.3845***	**0.3733***	**0.562***	**0.6662***	**0.7961***	**0.4761***
McFadden pseudo-R^2	0.29	0.14	0.34	0.31	0.27	0.29	0.31	0.38	0.28	0.24	0.22	0.18	0.27

Note: $^{*}p$-value <0.0001, $^{**}p$-value <0.001, $^{***}p$-value <0.01, and $^{****}p$-value <0.05. Values that are significant at 0.05 are in bold.
[a]Tables 3 and 4 contain variable definitions.

Table 6. Water supply adaptation models

Variable[a]	Lake water, y_{lake}	Government water, y_{govt}	Tank water, y_{tank}	Stored in tub, y_{tub}	Bottled water, y_{bottle}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
ASC RP	**−3.3082***	**−4.2924***	**−2.5535***	**−1.4573***	**−2.1862***	**−2.9496***	**−0.2457**	**−1.8728***	**−1.7191***	**−1.3399***	**−2.5251***
Outage duration, x, dur	**0.0019***	**0.002***	**0.0008***	**0.0006***	**0.0005****	−0.0002	**−0.0009***	**0.0023***	**0.0025***	**0.0028***	**0.003***
Water usage 1, x, w.use1	1.2879	−0.5353	0.8413	**0.9601******	−0.693	−0.4714	−0.1181	0.5404	0.3461	0.3865	0.0528
Water usage 2, x, w.use2	**1.3982******	−0.0388	0.657	0.1133	**−0.7937******	0.1812	−0.2675	0.2634	0.561	−0.0995	0.4707
Water usage 3, x, w.use3	**0.7081******	−0.1264	**0.5595******	**0.829***	0.1818	0.0063	−0.0112	0.0988	−0.1303	−0.2552	−0.2112
Water usage 4, x, w.use4	**1.7124*****	0.5215	0.7502	**0.9899****	0.1244	0.4731	0.4696	**0.7574*****	**0.6451******	**0.5358******	**1.4084****
Water sources, x, w.source	−0.2035	−0.0878	0.2543	−0.1774	0.277****	0.0435	−0.1737	0.1907	−0.0309	0.147	0.0598
Water conservation, x, w.con	−0.0043	**0.3758******	0.2389	0.1934	0.1038	**0.4258*****	0.0689	−0.0685	−0.0226	−0.2608****	−0.0475
Emergency likely, x, l.emer	−0.2584	0.1409	−0.0659	0.0043	**0.2978******	0.3083	0.2383	−0.0033	−0.07	−0.0223	−0.1859
Emergency worry, x, w.emer	**0.4664******	0.1947	0.3174	0.144	0.1727	**0.32******	0.0204	−0.0236	0.1466	0.0655	0.1768
Emergency negative, x, n.emer	**−0.6701*****	−0.1371	**−0.4643******	−0.0632	**0.4255*****	0.1502	−0.0519	0.0585	0.0849	0.0793	−0.3568
Preparation, x, prep	0.0391	0.0028	**0.0995*****	**0.0936****	0.0283	**0.0561******	0.0183	0.0295	−0.0038	−0.0076	0.0469
Age, x, age	**−0.0468***	**0.0207*****	**−0.0421***	−0.0041	**0.0255***	**0.0264***	**0.0113******	**−0.0209****	**−0.0239***	**−0.0228***	**−0.0427***
Income, x, inc	**−0.004******	**−0.0043*****	−0.0004	−0.0005	0.0006	0.0019	−0.0012	−0.0013	0.0019	**0.0034****	**0.0029******
Gender 1, x, gen1	0.0443	−0.0273	−0.2456	**−0.3372******	**−0.4276*****	−0.1232	0.0669	**−0.3986*****	**−0.3881*****	**−0.5596***	−0.1153
Gender 2, x, gen2	0.0481	1.4191	−1.2721	−0.1417	−1.4038	0.0794	1.2812	−0.0284	−0.0439	−0.4722	−0.1073
Race 1, x, race1	**−1.1006******	**−0.9015******	−0.5224	**−0.7293******	−0.1379	**−0.9964*****	**−0.5756******	−0.4515	−0.4454	−0.2684	**−1.1661*****
Race 2, x, race2	−0.2155	−0.1537	−0.3569	−0.3667	−0.1365	**−0.7017*****	−0.283	**−0.5072*****	**−0.4704*****	**−0.8078***	**−0.862****
Race 3, x, race3	−0.6603	**1.1584******	−0.209	−0.5389	−0.5019	−1.0822	0.2789	−0.4984	**−1.0622******	**−0.9401******	**−1.7631******
Race 4, x, race4	−0.6744	−0.2916	−0.2365	−0.6171****	−0.0566	**−0.6467*****	−0.008	−0.1064	**−0.5651*****	**−0.3662******	−0.2184
Education, x, edu	0.0702	−0.1347	−0.097	**−0.4398*****	**0.4878****	**0.4125******	−0.0862	0.0589	**−0.2765******	−0.2155	**−0.5131******
Child, x, child	**0.5978******	0.2392	**0.6886*****	0.0009	0.1744	−0.0149	0.017	**0.3165******	**0.3546*****	0.0924	**0.4657******
Elders, x, elder	−0.3812	−0.383	−0.4304	0.014	−0.2837	0.0713	−0.0597	−0.2005	−0.1942	−0.2407	**−0.6488*****
Pets, x, pets	0.1221	−0.0645	0.1045	0.1065	0.1945	**0.3505******	0.2191	0.1436	0.0802	0.0835	−0.0676
Medical condition, x, med.c	0.2494	0.039	0.0694	0.151	−0.2846	0.0427	−0.3038	0.1068	−0.0927	0.0743	**0.5575******
Medical equipment, x, med.e	0.7082	0.4436	0.2912	0.1681	**−0.6018*****	**−0.8079****	−0.2399	−0.1261	**0.7718***	0.5127***	**0.7803******
Home owner, x, own	0.09	0.3053	0.1652	−0.2585	0.0361	0.0797	**0.4101******	−0.203	−0.0597	0.0601	−0.0926
House type 1, x, house1	0.0981	0.1621	−0.0358	0.0613	0.1708	0.1699	0.0201	0.2426	−0.1517	−0.0065	−0.0229
House type 2, x, house2	0.9699	0.1844	−0.1566	−0.5969	−0.6057	−0.54	−0.3491	**−0.9597*****	−0.6489	−0.2994	−0.159
Years home, x, yr.h	0.0162	−0.0099	−0.0044	0.0024	−0.0043	−0.0014	−0.0077	−0.0058	0.0012	−0.0069	0.0028
Years county, x, yr.c	0.0036	−0.0015	0.0078	−0.0112	0.0054	0.0026	−0.0059	**0.0108******	0.0026	0.0047	−0.0043
Employment status, x, employ	−0.0234	**0.3845******	−0.0412	**−0.3526******	0.0124	**−0.4388*****	**−0.4057*****	−0.1372	−0.0424	0.0031	0.0612
Marital status, x, marital	0.4189	0.1227	0.2574	0.2072	**−0.3862******	−0.0628	−0.0125	−0.1954	**-0.4351*****	0.0102	−0.0867
Reliable people, x, rel	−0.0223	**0.1326******	0.0973	0.0419	**0.2419***	**0.1527*****	**0.1614*****	**0.2532***	**0.2258***	0.0219	0.0366
Neighborhood con., x, neigh	−0.3335	0.1389	−0.0566	0.0298	−0.0726	−0.2212	0.1064	−0.0403	0.142	0.1402	−0.1346
State dependence, φ_i, mean	**1.6045***	0.2422	**0.8199*****	**1.0929***	−0.0534	0.2589	**0.3194*****	0.0671	0.1094	0.1808	**0.9357***
State dependence, φ_i, standard deviation	0.1431	0.1713	0.0542	0.0721	**0.4741******	0.1848	0.0921	0.1473	0.1446	0.0426	**0.303******
SP scale relative to RP, λ	**0.3178***	**0.4589***	**0.3285***	**0.4055***	**0.4603***	**0.3677***	**0.4097***	**0.5373***	**0.6278***	**0.6757***	**0.4319***
McFadden pseudo-R^2	0.34	0.28	0.32	0.24	0.21	0.28	0.22	0.21	0.19	0.17	0.28

Note: $^{*}p$-value <0.0001, $^{**}p$-value <0.001, $^{***}p$-value <0.01, and $^{****}p$-value <0.05. Values that are significant at 0.05 are in bold.
[a]Tables 3 and 4 contain variable definitions.

Table 7. AMEs for electric power adaptation explanatory variables that are statistically significant at $a = 0.05$

Variable	Power generator, y_{gen}	Candles/ flashlight, y_{candle}	Heater/ fireplace, y_{heater}	Stove, y_{stove}	Car, y_{car}	Coffee shop, y_{shop}	Center, y_{center}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
Outage duration, x, dur	2.85×10^{-4}	-2.53×10^{-4}	—	-5.0×10^{-5}	-9.4×10^{-5}	1.27×10^{-4}	2.98×10^{-4}	-2.96×10^{-5}	-8.93×10^{-5}	3.20×10^{-4}	4.30×10^{-4}	3.40×10^{-4}	1.89×10^{-4}
Electricity usage 1, x, e.use1	—	—	—	—	—	—	—	—	—	—	—	0.0919	—
Electricity usage 2, x, e.use2	—	0.0659	—	—	0.0463	0.0966	—	0.0507	0.0932	—	—	—	—
Electricity usage 3, x, e.use3	0.1135	—	0.1596	—	—	0.1177	0.2177	—	—	—	0.1311	0.1226	0.1180
Electricity sources, x, e.source	—	0.0433	—	0.0575	0.0364	—	—	0.0537	0.0620	—	—	—	—
Electricity conservation, x, e.con	0.0579	0.0360	—	0.0856	0.0403	0.0415	—	0.0638	0.0692	—	—	—	−0.0307
Emergency likely, x, l.emer	—	0.0412	—	—	0.0303	—	—	0.0361	0.0531	—	—	—	—
Emergency worry, x, w.emer	—	—	—	—	—	0.0623	0.0698	—	—	—	—	—	—
Emergency negative, x, n.emer	—	—	—	—	—	—	—	—	0.0486	—	—	—	—
Preparation, x, prep	0.0131	0.0048	—	0.0085	—	—	0.0118	—	—	—	—	—	0.0057
Age, x, age	−0.0086	—	−0.0066	−0.0014	0.0012	—	—	—	—	−0.0042	−0.0031	−0.0033	−0.0050
Income, x, inc	—	—	—	—	—	—	—	—	—	—	0.0004	0.0008	0.0004
Gender 1, x, gen1	—	−0.0474	—	—	—	—	−0.0636	—	—	−0.0930	—	—	—
Gender 2, x, gen2	—	—	—	—	−0.2500	—	—	—	—	—	—	—	—
Race 1, x, race1	—	—	—	—	—	—	—	—	−0.0804	—	—	—	−0.0688
Race 2, x, race2	—	0.0857	—	—	—	—	—	—	—	−0.0629	−0.1001	−0.0987	−0.0618
Race 3, x, race3	—	—	—	—	—	—	−0.2254	—	—	—	−0.1820	—	—
Race 4, x, race4	0.0788	—	—	—	—	—	—	—	—	—	−0.1082	−0.0636	—
Education, x, edu	−0.0555	0.0719	—	—	—	0.0491	—	—	—	—	—	—	−0.0672
Child, x, child	0.0599	—	—	—	0.0278	—	0.0742	—	—	0.0534	0.0873	—	—
Elders, x, elder	—	—	—	—	—	—	—	—	—	—	—	—	−0.0373
Pets, x, pets	—	—	—	—	0.0419	—	—	0.0491	0.0513	—	—	—	—
Med. condition, x, med.c	—	—	0.1226	—	—	—	0.1311	—	—	—	—	—	0.0381
Med. equipment, x, med.e	—	—	—	—	—	−0.0854	—	—	−0.0587	—	0.0765	—	0.0616
Home owner, x, own	0.0672	—	—	—	—	—	—	—	0.0622	—	—	—	—
House type 1, x, house1	—	—	—	0.0657	—	−0.0578	—	—	—	—	—	—	—
House type 2, x, house2	—	—	0.1802	—	—	—	—	—	—	—	—	—	—
Years home, x, yr.h	—	—	—	—	−0.0012	—	—	—	—	−0.0026	—	—	—
Years county, x, yr.c	—	0.0014	—	0.0014	—	—	−0.0036	—	—	—	—	—	—
Employment status, x, employ	—	—	—	—	—	—	—	—	—	—	—	—	—
Marital status, x, marital	0.0960	—	—	—	—	—	0.0713	—	—	—	—	—	0.0483
Reliable people, x, rel	—	0.0168	—	0.0174	0.0115	0.0262	—	0.0128	—	0.0514	0.0287	—	—
Neighborhood con., x, neigh	—	—	—	—	—	—	—	—	—	—	—	—	—

Table 8. AMEs for water supply adaptation explanatory variables that are statistically significant at $a = 0.05$

Variable	Lake water, y_{lake}	Government water, y_{govt}	Tank water, y_{tank}	Stored in tub, y_{tub}	Bottled water, y_{bottle}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
Outage duration, x, dur	2.69×10^{-4}	3.10×10^{-4}	1.48×10^{-4}	$1.29 \times 10_{-4}$	5.45×10^{-5}	—	-1.9×10^{-4}	4.89×10^{-4}	4.43×10^{-4}	4.17×10^{-4}	2.85×10^{-4}
Water usage 1, x, w.use1	—	—	—	0.2071	—	—	—	—	—	—	—
Water usage 2, x, w.use2	0.2286	—	—	—	−0.0919	—	—	—	—	—	—
Water usage 3, x, w.use3	0.1116	—	0.1052	0.1793	—	—	—	—	—	—	—
Water usage 4, x, w.use4	0.2815	—	—	0.2133	—	—	—	0.1497	0.1248	0.0991	0.2123
Water sources, x, w.source	—	—	—	—	0.0238	—	—	—	—	—	—
Water conservation, x, w.con	—	0.0457	—	—	—	0.0476	—	—	—	−0.0452	—
Emergency likely, x, l.emer	—	—	—	—	0.0287	—	—	—	—	—	—
Emergency worry, x, w.emer	0.0706	—	—	—	—	0.0355	—	—	—	—	—
Emergency negative, x, n.emer	−0.0977	—	−0.0847	—	0.0376	—	—	—	—	—	—
Preparation, x, prep	—	—	0.0189	0.0204	—	0.0058	—	—	—	—	—
Age, x, age	−0.0084	0.0029	−0.0085	—	0.0029	0.0035	0.0026	−0.0042	−0.0048	−0.0043	−0.0065
Income, x, inc	−0.0005	−0.0008	—	—	—	—	—	—	—	0.0007	0.0004
Gender 1, x, gen1	—	—	—	−0.0710	−0.0400	—	—	−0.0813	−0.0723	−0.0965	—
Gender 2, x, gen2	—	—	—	—	—	—	—	—	—	—	—
Race 1, x, race1	−0.1591	−0.1236	—	−0.1534	—	−0.1048	−0.1297	—	—	—	−0.1464
Race 2, x, race2	—	—	—	—	—	−0.0680	—	−0.1011	−0.0899	−0.1443	−0.1138
Race 3, x, race3	—	0.0906	—	—	—	—	—	—	−0.1924	−0.1650	−0.1987
Race 4, x, race4	—	—	—	−0.1306	—	−0.0617	—	—	−0.1073	−0.0688	—
Education, x, edu	—	—	—	−0.0935	0.0484	0.0484	—	—	−0.0519	—	−0.0662
Child, x, child	0.0925	—	0.1327	—	—	—	—	0.0645	0.0665	—	0.0584
Elders, x, elder	—	—	—	—	—	—	—	—	—	—	−0.0756
Pets, x, pets	—	—	—	—	—	0.0401	—	—	—	—	—
Medical condition, x, med.c	—	—	—	—	—	—	—	—	—	—	0.0725
Medical equipment, x, med.e	—	—	—	—	−0.0644	−0.1057	—	—	0.1497	0.0933	0.1075
Home owner, x, own	—	—	—	—	—	—	0.0910	—	—	—	—
House type 1, x, house1	—	—	—	—	—	—	—	—	—	—	—
House type 2, x, house2	—	—	—	—	—	—	—	−0.1854	—	—	—
Years home, x, yr.h	—	—	—	—	—	—	—	—	—	—	—
Years county, x, yr.c	—	—	—	—	—	—	—	0.0022	—	—	—
Employment status, x, employ	—	0.0471	—	−0.0738	—	−0.0484	−0.0892	—	—	—	—
Marital status, x, marital	—	—	—	—	−0.0369	—	—	—	−0.0806	—	—
Reliable people, x, rel	—	0.0169	—	—	0.0249	0.0181	0.0367	0.0521	0.0409	—	—
Neighborhood con., x, neigh	—	—	—	—	—	—	—	—	—	—	—

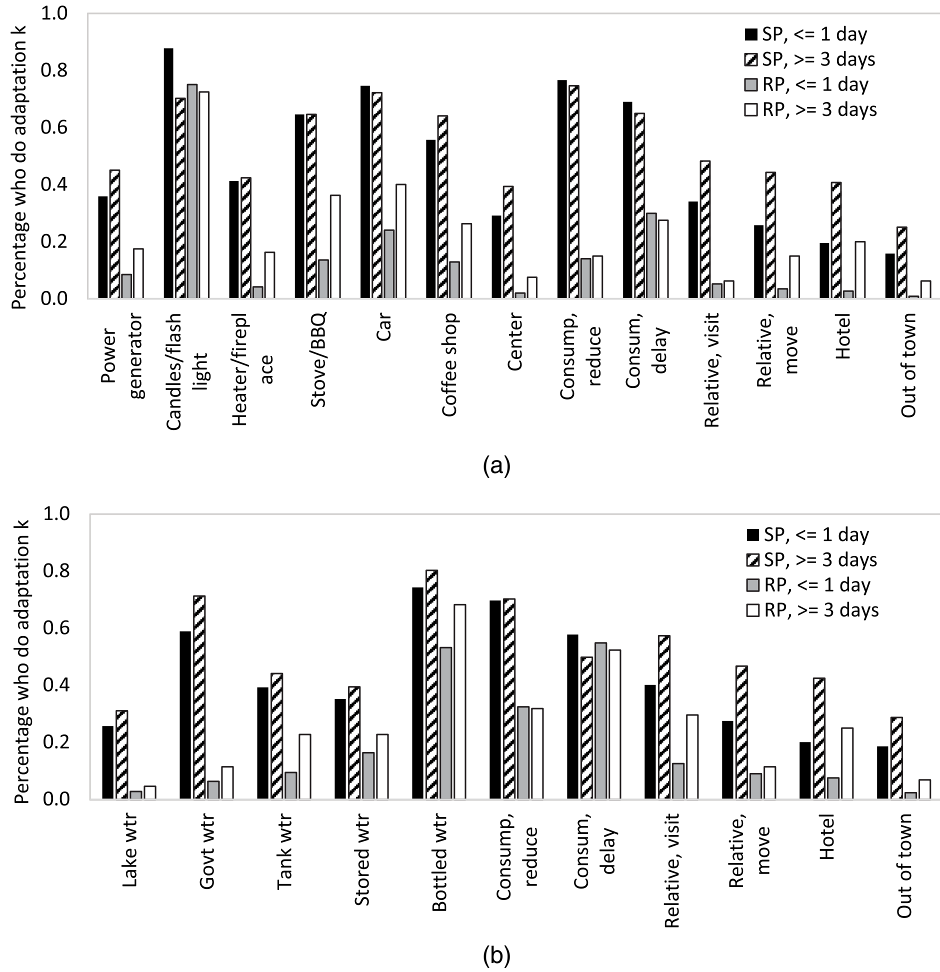

Fig. 1. Percentage of respondents who said they did or would do each of the following, by RP/SP and outage duration: (a) electric power adaptation; and (b) water adaptation.

common electric power adaptation, with approximately 3 out of 4 people saying they have or would use them. Using bottled water, y_{bottle}, is the most common water adaptation, with 53% saying they have done it for past outages of duration ≤ 1 day to 80% saying they would do it for future outages lasting at least 3 days. These are both relatively inexpensive, easy-to-implement efforts. In general, adaptations that require moving to a relative's/friend's, hotel, or out of town (y_{move}, y_{hotel}, y_{town}) are the least common of those investigated, although they are about 2–7 times more likely for outages of at least 3 days than for those that are no more than 1 day long. These results can provide utilities and emergency response organizations an estimate of how likely it is that consumers will implement various adaptations.

With the exception of using candles/flashlights (y_{candle}) in a power outage and using bottled water (y_{bottle}) or delaying consumption (y_{delay}) in a water outage, respondents suggested much higher likelihoods of doing adaptations in hypothetical future outages (SP) than in past outages (RP), even when controlling for the outage duration. It is worth examining the reasons for the difference in future work.

Effect of Infrastructure Type

Research question 2a asks *How does household adaptation implementation vary with infrastructure type?* The fact that six of the adaptations investigated can be applied in the case of either an electric power or water outage provides an opportunity to examine the effect of infrastructure type on implementation of those adaptations. In particular, for the six adaptations that apply to both infrastructure systems (Table 1)—$y_{\text{red}uce}$, y_{delay}, y_{visit}, y_{move}, y_{hotel}, y_{town}—we fitted an additional model in which we pooled electric power and water observations and added two binary variables, $z_{RP,it} = x_{\text{type}}\kappa_{RP,it}$ and $z_{SP,it} = x_{\text{type}}(1 - \kappa_{RP,it})$, to indicate which infrastructure system individual i's choice situation t was associated with and whether the choice situation was RP or SP. The variables $x_{e.\text{use}}$ and $x_{w.\text{use}}$ were replaced with a single variable, x_{use}, that has three levels: no (0), one (1), and at least two (2) special usages, respectively. For the new model with pooled observations, the statistically significant AMEs associated with the variables $z_{RP,it}$ and $z_{SP,it}$ ($\alpha = 0.05$) suggest that people are more likely to do adaptations in the case of water compared to electric power outages (Table 9). At the extreme, people are nearly 18 percentage points more likely to visit a relative's/friend's house for a water outage than an electric power outage. The impact of infrastructure type depends on whether the outage is a real past event or hypothetical future one. This is particularly true when it comes to delaying consumption, in which case people are 17.5 percentage points more like to delay consumption for a real water outage than a real electric power outage, while they are 14.6 percentage points less likely to delay consumption for a hypothetical water outage than a

Table 9. Main results of the pooled observations model

Result	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
AME of past water outage, z_{RP}	0.110	0.175	0.178	0.125	0.131	—
AME of future water outage, z_{SP}	—	−0.146	0.108	0.030	—	0.022
McFadden pseudo-R^2	0.33	0.24	0.23	0.24	0.21	0.29

hypothetical electric power outage. Comparing the R^2 values in Table 9 to those in Tables 5 and 6 suggests that pooling electric power and water observations does not change the goodness-of-fit substantially.

Effect of Outage Duration

To address Research question 2b—*How does household adaptation implementation vary with outage duration?*, we examine the coefficients and AMEs of the outage duration variable, x_{dur}, for each adaptation model (Tables 7 and 8). Outage duration, x_{dur}, was highly significant ($p < 0.0001$) for all adaptation models except using a nonelectric heater and/or fireplace, y_{heater}, in an electric power outage ($p = 0.752$) and reducing consumption, y_{reduce}, for water ($p = 0.106$). For electric power outages, in general, adaptations that could be done at home are less likely as the outage duration increases, while those that require going somewhere are more likely as the outage duration increases (Table 7). For example, for each week (168 h) longer an outage lasts, an individual is 4.6 percentage points less likely to use candles, flashlight, and/or lantern (y_{candle}) and 7.2 percentage points more likely to move to a relative's/friend's house (y_{move}) (Table 7). For water outages, however, all adaptations (except delaying consumption) are more likely as an outage lasts longer. An individual is 8.2 percentage points more likely to visit a relative's/friend's house (y_{visit}) for each additional week of outage duration (Table 7).

Fig. 2 offers another way to examine the effect of outage duration on the probability of doing each adaptation k. Consider one of the electric power adaptation curves in Fig. 2. To generate a point on that curve, using all electric power observations in the sample data, we set the outage duration to have a specified value, leaving all other variables at their original values; computed the probability individual i would do that adaptation [Eq. (3)]; and took the average over all observations. We generated the curve by repeating the process for multiple specified outage duration values x_{dur}. The curves for the water supply adaptations were computed similarly. Fig. 2 indicates that the effect of outage duration varies a lot by adaptation. For a few adaptations (use of candles/flashlight y_{candle}, charging phone in the car y_{car}, delaying consumption y_{delay}), the probability of doing it decreases with outage duration. For some (using a heater/fireplace y_{heater}, using a stove y_{stove}, using water from lake/river/creek y_{lake}, using water from a tank/rain barrel y_{tank}, and reducing consumption y_{reduce}) there is little effect of outage duration. For the other 10, implementation increases with outage duration. The probability of using candles/flashlight is particularly sensitive to outage duration, decreasing by half from 0.79 for an outage less than a day to 0.41 for a month-long outage. The likelihood of visiting a relative's/friend's for a water outage (y_{visit}) increases substantially from 0.11 to 0.37 as outage duration increases. Fig. 2 also shows the relative commonness of the various adaptations. For many, it suggests no more than 20% of respondents are likely to do them, no matter the outage duration. Using candles/flashlights, buying bottled water, and delaying consumption are the most popular adaptations.

Effect of Service Usage Characteristics

Another potential influence on likelihood of adaptation is the individual's service usage pattern. To address Research question 2c—*How does household adaptation implementation vary with use*

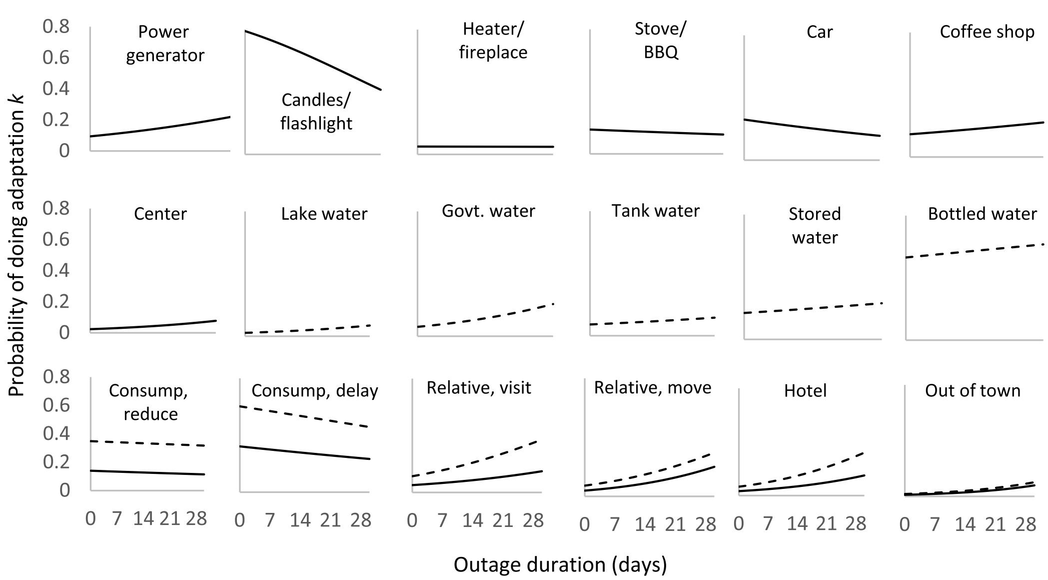

Fig. 2. Probability of doing adaptation k versus outage duration for electric power adaptations (solid lines) and water adaptations (dashed lines).

of service?—we examine the coefficients and AMEs associated with related variables, in particular, if the individual uses the service (electric power or water) for special uses ($x_{e.use}$, $x_{w.use}$), if the individual has an alternative source of the service in normal times ($x_{e.source}$, $x_{w.source}$), and the extent to which they have conserved the service in the past ($x_{e.con}$, $x_{w.con}$).

Using electric power for special uses (i.e., medical devices and/or work and business) has a large effect on the likelihood of implementing many adaptations. At least one of the three variables are statistically significant at $\alpha = 0.05$ for 11 of the 13 adaptations, and the AMEs are substantial (Table 7). At the extreme, using electricity for both medical devices and work uses makes an individual 21.8 percentage points more likely to go to a cooling/warming center. The same is true for water (Table 8). In particular, using water for at least two special uses (medical devices, work and business, and/or swimming pool/hot tub) is associated with one being substantially more likely to use stored or lake water, or to do an adaptation that requires leaving the home.

There is evidence that preevent conservation habits are also associated with an increased likelihood of implementing adaptations. Those who conserved to a larger extent in the previous five years were more likely to do many home-based electric power adaptations, and a little less likely to move out of town (electric) or move to a hotel (water).

Household Characteristics

Implementation of adaptations depends in part on the resources available to do them and the importance of the service, both of which suggest that the likelihood of implementing an adaptation varies across households. Research question 3—*What household characteristics are associated with implementation of different household adaptations?*—addresses this issue. In general, the influence of household characteristics varies greatly across adaptations (Tables 7 and 8).

The following are household characteristics with the largest effects on adaptation likelihood (Tables 7 and 8). Having someone with a medical condition increases the chance of using a heater and/or fireplace (y_{heater}) or going to a cooling or warming center (y_{center}) by 12 and 13 percentage points, respectively. Race has a large influence for electric power as well, with Hispanic and White respondents being 10 percentage points less likely to move to a friend's/relative's house (y_{move}) than Asian respondents. For water, Asians are more likely to do adaptations in general, especially those that require moving (y_{move}, y_{hotel}, y_{town}). Households with a child are 13 percentage points more likely to use water from a private tank or rain barrel (y_{tank}), and those with someone in the household who relies on medical equipment ($x_{med.e}$) are 11 percentage points less likely to adapt by reducing usage, and 11 and 15 percentage points more likely to move out of town (y_{town}) or move to a friend's/relative's house (y_{move}), respectively.

Other findings related to electric power adaptations and household characteristics include that women are more likely to use a candle/flashlight (y_{candle}), go to a warming/cooling center (y_{center}), or visit a relative's/friend's (y_{visit}); more educated people are more likely to use a generator (y_{gen}) or move out of town (y_{town}); people with higher income are more likely to do adaptations that involve moving; people with elders in the household are less likely to move out of town (y_{town}); homeowners are more likely to use a generator (y_{gen}) or delay consumption (y_{delay}); and people newer to their home are less likely to go to a friend's/relative's house for help (y_{visit}). In general, people are more likely to do various adaptations if they are younger, think an emergency is likely, worry about an emergency, have prepared more, and have more people to rely on for assistance. As one might expect, people are especially more likely to visit a relative's or friend's house for their heat or air conditioning (AME = 0.051) and more likely to move to a relative's or friend's house (AME = 0.029) if they have more people to rely on for assistance (x_{rel}) (Table 7).

For water, the effect of age varies by adaptation, with older people more likely to use government (y_{govt}) or bottled water (y_{bottle}) or reduce or delay consumption (y_{reduce} or y_{delay}), and younger people more likely to do the other adaptations. People with higher income are more likely to go to a hotel (y_{hotel}) or move out of town (y_{town}); those with lower income are more likely to use water delivered by the government (y_{govt}) or water from lakes, rivers, creeks (y_{lake}). In addition, more educated people are more likely to move out of town (y_{town}) or move to a relative's/friend's house (y_{move}), or to use water stored in a bathtub and/or pool (y_{tub}); people with elders in the household are less likely to move out of town (y_{town}); people who have lived in the county longer are more likely to go to a relative's/friend's house for help (y_{visit}); married people are less likely to move to a relative's/friend's house (y_{move}); and those who have done more preparation are more likely to do home-based adaptations. In general, people are more likely to do various water adaptations if they are women or have more people to rely on for assistance. People are especially more likely to visit a relative's or friend's house for their water and/or laundry facilities (AME = 0.052) and more likely to move to a relative's or friend's house (AME = 0.041) if they have more people to rely on for assistance (x_{rel}) (Table 8).

Adaptation Groupings

So far each of the 24 adaptations have been analyzed separately. Recognizing that an individual may implement more than one adaptation in the course of an outage, Research question 4 asks, *Which household adaptations tend to occur together? Which tend not to?* To begin to address this question, we use a symmetric association rule metric called *lift* defined as (Hahsler et al. 2005)

$$\text{lift}(X \Rightarrow Y) = \text{lift}(Y \Rightarrow X) = P(X \cap Y)/P(X)P(Y) \qquad (4)$$

Lift measures how many times more often X and Y occur together than expected if they were statistically independent. In this application, X and Y are individual adaptations, and $\text{lift}(X \Rightarrow Y)$ is used to measure the extent to which individuals indicating they did X were less or more likely to indicate they did Y as well (and vice versa). Tables 10 and 11 present the lift values for all combinations of electric power adaptations and water adaptations, respectively, based on RP choice situations (i.e., actual past outages).

For electric power, Table 10 shows that the lowest lift values involve the use of candles/flashlight (y_{candle}) and delaying consumption (y_{delay}), especially in association with adaptations involving leaving home (y_{hotel}, y_{town}). This makes sense because a person adopting the latter two adaptations is likely to have normal access to electricity, in which case there is no need for such an adaptation as using candles/flashlight or delaying consumption. The highest lift values between electric power adaptations involve moving out of town (y_{town}), especially in association with staying at a relative's/friend's house (y_{move}), hotel (y_{hotel}), or cooling/warming center (y_{center}), probably because individuals who go out of town must usually stay at one of these three places. Similarly, for water, individuals tend not to both go to a hotel and reduce water consumption (Table 11, lift = 0.6), but using water from lakes, rivers, and/or creeks (y_{lake}) tended to co-occur with using water delivered by the government (y_{govt}) (Table 11, lift = 7.0).

Table 10. Matrix of lift($X \Rightarrow Y$) for all combinations of electric power adaptations, where X is row and Y is column

Adaptation	Power generator, y_{gen}	Candles/ flashlight, y_{candle}	Heater/ fireplace, y_{heater}	Stove, y_{stove}	Car, y_{car}	Coffee shop, y_{shop}	Center, y_{center}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
Power generator, y_{gen}	—	0.91	3.62	1.70	1.25	1.11	2.21	1.45	0.88	1.14	2.04	2.93	4.14
Candles/flashlight, y_{candle}	—	—	0.92	1.10	1.09	1.07	0.98	1.01	1.05	1.06	0.89	0.57	0.58
Heater/fireplace, y_{heater}	—	—	—	2.92	2.31	2.61	3.39	2.33	1.10	2.09	3.01	5.81	7.63
Stove, y_{stove}	—	—	—	—	2.01	1.98	1.78	1.42	1.58	1.57	1.48	2.04	1.67
Car, y_{car}	—	—	—	—	—	2.08	2.13	1.51	1.31	1.76	1.48	1.87	2.25
Coffee shop, y_{shop}	—	—	—	—	—	—	3.64	2.42	1.61	2.57	2.16	1.19	1.36
Center, y_{center}	—	—	—	—	—	—	—	2.37	1.23	4.47	4.82	1.77	8.14
Reduce consumption, y_{reduce}	—	—	—	—	—	—	—	—	2.26	1.78	1.84	1.31	0.89
Delay consumption, y_{delay}	—	—	—	—	—	—	—	—	—	1.68	0.87	0.68	1.26
Relative, visit, y_{visit}	—	—	—	—	—	—	—	—	—	—	3.19	1.95	3.59
Relative, move, y_{move}	—	—	—	—	—	—	—	—	—	—	—	5.41	9.04
Hotel, y_{hotel}	—	—	—	—	—	—	—	—	—	—	—	—	14.95
Out of town, y_{town}	—	—	—	—	—	—	—	—	—	—	—	—	—

Table 11. Matrix of lift($X \Rightarrow Y$) for all combinations of water adaptations, where X is row and Y is column

Adaptation	Lake water, y_{lake}	Government water, y_{govt}	Tank water, y_{tank}	Stored in tub, y_{tub}	Bottled water, y_{bottle}	Reduce consumption, y_{reduce}	Delay consumption, y_{delay}	Relative, visit, y_{visit}	Relative, move, y_{move}	Hotel, y_{hotel}	Out of town, y_{town}
Lake water, y_{lake}	—	6.96	4.43	4.35	1.10	1.24	0.98	2.38	5.80	3.70	9.94
Government water, y_{govt}	—	—	3.25	2.54	1.00	0.79	0.73	1.23	2.80	2.86	5.33
Tank water, y_{tank}	—	—	—	2.59	0.84	0.84	0.77	1.30	2.57	1.62	3.39
Stored in tub, y_{tub}	—	—	—	—	1.15	1.23	1.08	1.30	2.10	1.51	2.12
Bottled water, y_{bottle}	—	—	—	—	—	1.33	1.14	1.38	1.03	1.02	0.92
Reduce consumption, y_{reduce}	—	—	—	—	—	—	1.37	1.57	0.84	0.59	1.10
Delay consumption, y_{delay}	—	—	—	—	—	—	—	1.13	0.99	0.90	0.78
Relative, visit, y_{visit}	—	—	—	—	—	—	—	—	5.07	4.24	9.48
Relative, move, y_{move}	—	—	—	—	—	—	—	—	—	2.31	3.88
Hotel, y_{hotel}	—	—	—	—	—	—	—	—	—	—	4.76
Out of town, y_{town}	—	—	—	—	—	—	—	—	—	—	—

Discussion and Conclusions

This paper presents a number of findings about how people adapt, or might adapt, to interruptions in electric power and water service. In general, adaptations that are cheaper or more easily implemented with day-to-day materials or habits are widely anticipated. Moving tends to be more difficult but is prevalent if the outage lasts 3 days or more. Predictors of adaptation vary greatly across adaptation types. A number of predictors were identified, though, including outage duration, infrastructure type, whether the service is used for medical devices or work, if the individual tended to conserve preevent, and many individual characteristics, including income, race, and number of people who can be relied on for assistance. Some adaptations tend to occur together and some tend not to.

Several large-scale curtailments of electricity and water have occurred in the last few years, owing to hazard impacts (e.g., Hurricanes Harvey and Irma); maintenance shortfalls (North Texas ice storm); or hazard mitigation (power cutoffs to prevent wildfires). While a number of studies have looked at how people adapt, and sometimes the relative sufficiency of these adaptations, there are fewer that have attempted to quantify the description of those adaptations or project them to potential outages of longer duration.

We anticipate several possible implications from this study and from others like it. In particular, by mapping out the range of possible adaptations, who adopts them, and when they might be implemented or discontinued in favor of others, emergency managers will have better insight into a possible postdisaster environment. Knowing what to expect, in turn, can have some subsidiary benefits, which might include planning that takes into account a fuller range of human behavior. During an event, knowing what people have done elsewhere can alert crisis managers of what to expect, rendering the situation that much less strange and disorienting, and might also suggest ways to support emergent efforts. The adaptations that people employ are examples of *bricolage* (Weick 1993), where people create ways of solving problems with what is at hand. The collective bricolage of the grassroots civil society, blended with the efforts of disaster-management institutions, should bolster community resilience and overall societal functioning.

The analysis herein offers many opportunities for future work. While the relationship between outage duration and adaptation implementation was studied here, there is still much about the timing of adaptations that is not known. In particular, further study is warranted to learn when adaptations are first implemented, when they might be discontinued (because it becomes too costly, for example), and if they are implemented continuously during an outage or periodically. While the adaptations were considered mostly individually in this study, one could examine whether natural groupings tend to be implemented simultaneously, or in succession. Additional empirical studies of more types of infrastructure systems, more types of events, and for more geographic locations could help reveal the extent to which adaptations vary over those circumstances and the extent to which the findings herein are transferable to other situations. An event type was not specified in the survey used in this study, but as it was deployed only in Los Angeles County, California, certain types of outage events are more likely than in other places (e.g., earthquakes and wildfires, not hurricanes or winter storms). This analysis focused on residential users of utility services. Commercial, industrial, and other users implement adaptations in the face of service interruptions as well, and merit similar study. Additional explanatory variables could be explored as well, such as those capturing differences among cities. RP data associated with longer outage durations, if available, would be valuable to test the findings of this analysis.

Data Availability Statement

All survey data that support the findings of this study are available from the corresponding author upon reasonable request.

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