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Household impacts of interruption to electric power and water services

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Abstract

Critical infrastructure systems derive their importance from the societal needs they help meet. Yet the relationship between infrastructure *system functioning* and *societal functioning* is not well-understood, nor are the impacts of infrastructure system disruptions on consumers. We develop two empirical measures of societal impacts—willingness to pay (WTP) to avoid service interruptions and a constructed scale of unhappiness, compare them to each other and others from the literature, and use them to examine household impacts of service interruptions. Focusing on household-level societal impacts of electric power and water service interruptions, we use survey-based data from Los Angeles County, USA, to fit a random effects within-between model of WTP and an ordinal logit with mixed effects to predict unhappiness, both as a function of infrastructure type, outage duration, and household attributes. Results suggest household impact increases nonlinearly with outage duration, and the impact of electric power disruptions is greater than water supply disruptions. Unhappiness is better able to distinguish the effects of shorter-duration outages than WTP is. Some people experience at least some duration of outage without negative impact. Increased household impact was also associated with using electricity for medical devices or water for work or business, perceived likelihood of an emergency, worry about an emergency, past negative experiences with emergencies, lower level of preparation, less connection to the neighborhood, higher income, being married, being younger, having pets, and having someone with a medical condition in the house. Financial, time/effort, health, and stress concerns all substantially influence the stated level of unhappiness.

Keywords Infrastructure system · Lifeline · Outage · Electric power · Water · Household

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1 Introduction

Civil infrastructure systems, such as electric power and water supply systems, provide essential goods and services to meet societal needs. The ultimate goal of these systems—in fact, what makes them critical—is their role in societal functioning. Recognizing this, multiple agencies and researchers have increasingly acknowledged the importance of better understanding the relationship between *system functioning* and *societal functioning*, where the former refers to the provision of the service from a network of pipes or power lines (e.g., percentage of customers receiving water or power), and the latter refers more generally to the ability of industries and businesses to operate; emergency services to perform their duties; households to participate in or get to work, school, and leisure activities; individuals to drink, bathe, and live their daily lives (NEHRP 2014, ATC 2016, NIST 2016, Hasan and Foliente 2015; Davis 2019, 2021; Rojahn et al. 2019). Describing this relationship more fully could provide a clear basis for defining infrastructure system performance goals expressed in terms of societal functions, assessing the current performance of the nation's infrastructure systems in societal terms, and developing design and operations methods to achieve the expressed societal performance goals.

Nevertheless, developing such an understanding is made difficult by the complexity of the system-societal functioning relationship. The societal functioning consequences of system functioning interruption depend on the characteristics of the user (e.g., available resources and social capital to adapt), characteristics of the service interruption (e.g., other impacts it caused, geographic area affected), and context (e.g., climate). The relationship may not be linear. An hour without power may matter differently if it is the 100th hour than if it is the first (e.g., the associated cost function may be convex such that marginal costs increase over some time period). The concept of societal functioning is also multidimensional and no widely accepted, natural scale exists to measure it.

Perhaps because of these challenges, the way in which infrastructure system services meet societal needs, and the way interruptions of those services impair the ability to meet those needs are still not well-understood (Sattar et al. 2021, SFPURA 2009). In particular, there has been little empirical or quantitative investigation to understand the magnitude of household impacts, how they vary across disruptive events and household types, or what considerations govern the level of impact experienced. This paper contributes to the literature by helping to fill this gap.

In particular, focusing on household-level societal impacts of electric power and water service interruptions, and using survey-based data from Los Angeles County, in this paper, we develop two empirical measures of societal impacts, compare them to each other and others recently proposed in the literature, and use them to examine household impacts of service interruptions. In particular, we examine the following research questions:

- *Research Question 1.* How do household impacts vary with infrastructure system type and outage duration?
- *Research Question 2.* What household characteristics are associated with greater household impacts from electric power and water service interruptions?
- *Research Question 3.* What are the concerns that influence an individual's level of unhappiness associated with service interruptions?

Following a summary of literature related to societal impacts of infrastructure system disruptions in Sect. 2 and introduction of a conceptual framework to guide the analysis in

Sect. 3, we describe the data in Sect. 4 and the statistical models used in Sect. 5. The three research questions are examined in turn in Sect. 6, and the paper concludes with a discussion of the implications of the results and limitations of the analysis.

2 Societal impact literature

There is a relatively small though growing literature addressing societal impacts of infrastructure system disruptions directly (Petersen et al. 2020; Chang 2016). Previous work can be partitioned into two main approaches—macro and micro. The macro approach aims to understand impacts directly for a community or region as a whole; the micro approach aims to understand impacts for individual businesses, organizations, or households within a community. Both include theoretical and empirical efforts (1) to define metrics to represent societal impacts, and (2) to use those metrics to better understand them (e.g., magnitude; distribution across geographic areas, population groups, and time; relationship to impact as defined in engineering terms).

Davidson et al. (2022) discuss the macro approach and the micro approach more generally. Here we highlight the relatively few previous studies that share the focus of the current study, the effects of infrastructure system disruptions on households. Mostafavi and colleagues have explored the issue through a few recent papers using survey data from Harris County (home to Houston) in Hurricane Harvey (2017) (Dong et al. 2020, Esmalian et al. 2019; Dargin and Mostafavi 2020; Coleman et al. 2020). They introduced the concept of the *hardship* a household experienced as a measure of societal impact and defined it as a function of (1) extent of service disruption, and (2) a household's *tolerance* to withstand the disruption. Two thresholds of tolerance were introduced, the acceptable service level (need in daily life) and minimum adequate service level in a disaster setting. The degree of hardship was measured by asking survey respondents the degree of hardship experienced on a Likert scale (none at all (1) to a great deal (5)). Tolerance to service disruptions were measured by asking how many days they would be capable of tolerating the disruption. Dargin and Mostafavi (2020: 20) found differences in well-being impacts in various population groups. For example, low-income groups registered greater impacts. In their study, though, infrastructure disruptions in transportation, waste removal, food supplies, and water were of greater impact than electric and communications, possibly because these latter outages were of relatively shorter duration. Dong et al. (2020) examined the impact of disrupted access to healthcare facilities and further proposed a disruption tolerance index (DTI) to represent the extent to which disruption in a particular infrastructure system influences certain populations. Focusing on impacts of power outages, Esmalian et al. (2019) used agent-based simulation including a household agent whose tolerance was predicted in a negative binomial model as a function of household characteristics. Coleman et al. (2020) focused on inequality in exposure and hardship across population groups due to infrastructure service disruptions, considering transportation, power, communication, and water service. Dargin and Mostafavi (2020) extended the ideas to define household *well-being* as a function of duration of service disruption and hardship. Well-being, derived from the Personal Wellbeing Index (PWI) (IWG 2013), was measured by asking for Likert scale assessments (none at all (1) to a great deal (5)) indicating how often or how much they experienced seven feelings—helplessness, anxiousness, upsetting thoughts, safety, depression, daily life tasks, and feeling distant.

Yang et al. (2021) focused on individual physiological needs and incorporated adaptive capacity to evaluate the societal impact of disrupted water infrastructure, including a case study for Osaka, Japan. They define five levels of need satisfaction. In Level 1, for example, survival and hygiene needs can be met; drinking, cooking, washing, bathing, and laundry are assured. In Level 2, survival can be met and hygiene can mostly be met; drinking, cooking, washing are assured, and bathing and laundry are possible. Societal impact is then defined as the percentage of the population in each level. Adaptive capacity is considered by examining the availability of tap water, bottled water, and emergency water.

Petersen et al. (2020) address the related question of what the public (European citizens specifically) considers an acceptable level of disruption to critical infrastructure during a disaster. The study focused on essential goods, water, and transportation in the empirical analysis. Four below normal levels of service were defined (e.g., drinking water from tanks provided, need to boil before drinking) and respondents were asked for the maximum amount of time they would be willing to tolerate the disruption (hours, days, weeks, months, years, or not at all). Acceptability likely depends on the consequences associated with the service disruption, the ease with which someone can adapt to the disruption, and the associated costs with reducing it. If costs were not implicitly considered, i.e., there was no tradeoff, there would be no reason to tolerate any disruption.

Gardoni and Murphy (2010) and Tabandeh et al. (2018, 2019) offer a capability-based approach to describing societal impacts of disasters. Indicators represent the capabilities, which capture distinct dimensions of an individual's well-being, including for example, meeting physiological needs, earning income, being mobile, and being socially connected (Tabandeh et al. 2019). Though not directly related to the effects of disruption to infrastructure systems services, the modified domestic asset index (Bates and Peacock 1992; Arlikatti et al. 2010) and well-being losses in Walsh and Hallegatte (2019) offer alternative methods of measuring household impacts of disaster events that are more complete than repair costs to physical assets.

Together this previous work highlights interest in better understanding the effects of infrastructure system disruptions on households and offers a few possible ways to do so. The study herein adds to this nascent literature by using survey data from Los Angeles County to quantitatively examine household impacts of service interruptions using two alternative metrics, unhappiness and willingness to pay. The metrics and findings are compared to those recently proposed in the literature.

3 Conceptual framework and comparison of measures

Figure 1 provides a conceptual framework to facilitate discussion of possible household impact metrics. Service is often defined in binary terms as being provided or not, with a service interruption then defined in terms of its duration. To be more precise, normal service can also be described in terms of multiple *basic service categories* or dimensions of service that an infrastructure system provides, such as, delivery, collection, quantity, quality (Davis 2021). The level of service may be reduced then by interrupting one or more of those basic service categories for a period of time (e.g., if water is provided but is not potable or not at the usual pressure, or if electricity is provided but there are rolling blackouts or brownouts). The raw reduced level of service is the quantity often described in engineering studies that indicate outage duration or percentage of normal demand that could be

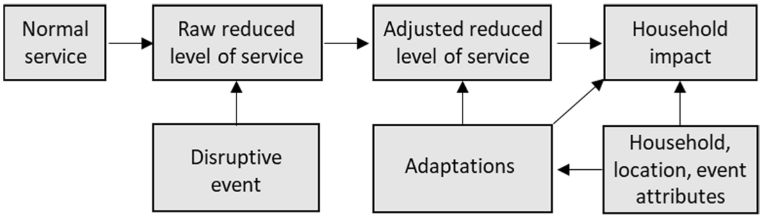


Fig. 1 Conceptual framework of infrastructure system disruption impact on household well-being

served after a disruptive event, *assuming no reaction from consumers (or possibly system operators)*.

In reality, when a reduction in level of service happens, adaptations occur in response (e.g., Palm 2009; Abbou et al. 2022). They may address a reduced level of service by reducing, delaying, or relocating consumption (e.g., skipping a shower, postponing laundry or doing it at a relative's house), or by augmenting supply (e.g., buying bottled water or using a generator). Adaptations may be implemented by the household or organizations in the community, as when a company provides warming/cooling centers. The infrastructure system operator implements adaptations as well, such as rerouting around damage or providing tanked water. Adaptations are often not a perfect replacement or substitute for the disrupted service. They may be possible only for a limited duration or may support some but not all uses of an infrastructure system service. Candles, for example, can substitute for the light provided by electricity, but not home heating or cooking. Thus, the combination of the raw reduced level of service and adaptations together determine the adjusted reduced level of service. While the *raw* reduced level of service is that provided by the networked system, the *adjusted* reduced level of service includes that provided by auxiliary sources and the adjusted demand. This is consistent with a substitution effect in economics, in which consumers alter their mix of service sources to the extent possible, to maintain a given level of utility.

Finally, that adjusted reduced level of service, described for example, in terms of the duration of interruption in one more basic service dimensions, can then be translated into the final impact on households, i.e., the effect of that reduced service on the household's ability to live its normal life. The difference between the adjusted reduced level of service and the household impact recognizes that an hour without electric power, for example, could have almost no noticeable effect for one household but a major life-threatening effect for another in other circumstances, for example, if it means an elderly person goes without heating or cooling in a severe climate. Both the type and extent of adaptations implemented and the relationship between adjusted reduced level of service and final household impact depend on attributes, including preferences, of the household (Petersen et al. 2020), and characteristics of the location and the event. They may differ, for example, if the disruptive event is widespread, causing many other regional effects, or more localized. They may differ based on the climate and population density of the location. The household impact may reflect both the adjusted reduced level of service and any cost in terms of finances, time, effort, or other resources, of implementing adaptations.

No consensus exists for how to measure the impact of service interruptions on households, but the recent literature suggests a few possibilities, and this paper uses two possible metrics new for this application (Sect. 2, Table 1). Three of the measures are disaggregated by level of need satisfaction or dimensions of personal well-being (societal

Table 1 Measures of household impact due to service interruption

Measure	Definition	Description	Reference(s)
Societal impact	Percentage of population in each level of need satisfaction (survival, hygiene, etc.) due to disrupted infrastructure	*Needs *Component-based	Yang et al. (2021)
Capability-based well-being	Indicators represent capabilities, which capture distinct dimensions of an individual's well-being, including, e.g., meeting physiological needs, earning income, being mobile, and being socially connected	*Needs *Component-based	Gardoni and Murphy (2010), Tabandeh et al. (2018, 2019)
Well-being	Measured in 5-point Likert (not at all to a great deal) for each of 7 measures (helplessness, anxiousness, upsetting thoughts, safety, depression, daily life tasks, feeling distant)	*Reaction *Component-based	Dargin and Mostafavi (2020)
Hardship	What was the extent of hardship your household experienced due to X service interruptions? [None, a little, moderate, a lot, a great deal]	*Reaction *Summary	Coleman et al. (2020), Dargin and Mostafavi (2020), Dong et al. (2020)
Tolerance	Amount of time a household can tolerate infrastructure service disruption X in a disaster	*Reaction *Summary	Coleman et al. (2020), Esmalian et al. (2019), Dong et al. (2020)
Acceptability	Maximum time they would be willing to tolerate a disruption (specified in terms of below normal service level scenarios)	*Reaction *Summary	Petersen et al. (2020)
WTP	How much would your household pay for a backup service that would have provided/would provide your normal level of service? [$]	*Reaction *Summary	This paper
Unhappiness	Considering actions taken to deal with disruption, as well as any remaining reduction in service, what level of unhappiness would/did you feel? [Not, slightly, moderately, very, extremely unhappy]	*Reaction *Summary	This paper

impact, well-being, capability-based well-being); the rest are summary measures providing an overall assessment of the impact. They are all self-reported measures and implicitly include the effect of both any reduced level of service that exists even after adaptations and any negative experience associated with implementing the adaptations (e.g., cost of a generator, or time spent getting water from a tanker truck) (Fig. 1).

Measures of the ultimate impact on households can be categorized into two groups, (1) needs-based and (2) reaction-based (Table 1). In the former, a list of needs the infrastructure system service helps a household meet are enumerated (e.g., survival, hygiene, earning income), and the impact is defined in terms of the extent to which those are met. The needs may be defined more specifically or generally, and their definition may depend on the infrastructure system and location (e.g., country). In the reaction-based measures, the impact of the service disruption is captured in terms of the household's emotional reaction to it, how they interpret the severity of the interruption and its implications. *Well-being* describes that reaction in a disaggregated way; the others are summary measures. In the cases of *Tolerance* and *Acceptability*, it is not clear what happens if a household does not tolerate or accept a service disruption. One could say they will not tolerate a disruption, but they may just have to if there is no alternative. There is an inherent tradeoff between service level and cost in terms of economic or other resources. It may be that an individual is displeased with a specified level of service, but if the choice is between that and investing substantial resources to improve it, they would rather accept it.

Willingness to pay (WTP) addresses this by framing the impact in terms of the tradeoff. However, it muddies the measure of household impact because it reflects both the hardship experienced as a result of a service disruption and the household's personal access to resources rather than only the former. For this reason, WTP is often used in economic studies of demand where the consumer must be willing and able to pay for a product or service. *Unhappiness* is most similar to *Hardship* as a reaction-based summary measure. Ultimately, the best metrics will depend on the particular application, which in turn determine the required ease of assessment, units desired (e.g., time, dollars), and applicability across infrastructure system types and locations. This paper aims to move the conversation forward by examining two metrics that are new for this application, WTP and unhappiness.

4 Data

4.1 Survey overview

The data used in this analysis were collected through a web-based (online) survey conducted May-December 2020. Designed to help understand individuals' responses to electric power and water supply service outages, the survey 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 future electric power and water service outages of varying durations; (4) risk perception, emergency preparedness, and social network; and (5) socio-demographics. Respondents completed the survey in an average of 23.5 min.

The quota-based survey sample was obtained through Qualtrics, a third-party survey vendor. Only respondents 18 years old and older living in Los Angeles County were considered eligible. The participants were recruited through Qualtrics panels, with incentives paid that included travel points and other remuneration. A census-representative sample was generated through quota Qualtrics panels; participants were recruited from multiple panels until the appropriate census population proportion was achieved based on characteristics usually found to be important in relevant studies of risk, preparedness, vulnerability, and resilience—age, gender, race, education, and income. Several checks were implemented to ensure high quality data, including checks against speeding through the survey, residents being located outside Los Angeles, straightlining, and providing gibberish answers. Responses showing these characteristics were omitted. 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%. All elements of the study design and instrumentation were reviewed by our university Institutional Review Board and approved as conforming to standards for informed consent.

4.2 Household societal impact and outage duration variables

Ten questions were asked to solicit information associated with a past outage, five for an electric power and five for a water supply outage (Fig. 2). Similarly, six questions were asked to solicit information associated with hypothetical future outages, three for electric power and three for water supply (Fig. 3). Questions 5 and 8 were based on a scenario adapted from Carlsson and Martinsson (2007, p79). Responses to these questions resulted in up to ten observations for each respondent (five outage durations each for electric power and water). Each observation included the WTP, y_{wtp}, and unhappiness, y_{un}, associated with a particular outage duration, x_{dur}. Note that the degree of unhappiness and WTP are designed to account for impact of the outage together with adaptive actions taken in response. Adaptations could provide a substitute for the infrastructure system service, but not necessarily at the same level and perhaps at a cost. Using a gas stove during an electric

Q1. Have you ever experienced an electricity [water] outage at your place of residence?

☐ Yes ☐ No

Q2. Approximately how long did the electricity [water] outage 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 day ☐ 1 week
☐ 1 hour ☐ 3 days ☐ 1 month
☐ 12 hours

Q3. Considering the actions you took to deal with the longest outage that you experienced, as well as any remaining reduction in service, what level of unhappiness did you feel as a result of the outage?

☐ Not unhappy ☐ Very unhappy
☐ Slightly unhappy ☐ Extremely unhappy
☐ Moderately unhappy

Q4. To what extent did each of the following concerns influence your level of unhappiness?

	Not at all	To a minor extent	To a moderate extent	To a major extent
Financial cost	☐	☐	☐	☐
Time or effort to meet household needs	☐	☐	☐	☐
Physical health effects	☐	☐	☐	☐
Stress	☐	☐	☐	☐

Q5. How much would you have paid for a backup service that would have provided your normal level of service during the longest outage that you experienced?

☐ Nothing ☐ Some amount (specify amount) $_________

Fig. 2 Questions to solicit information associated with a past outage

Q6. Considering everything you could do to satisfy your household needs, as well as any remaining reduction in service, what level of unhappiness would you feel if the outage lasted 1 day, 3 days, 1 week, and 1 month?

	Not unhappy	Slightly unhappy	Moderately unhappy	Very unhappy	Extremely unhappy
1 Day	☐	☐	☐	☐	☐
3 Days	☐	☐	☐	☐	☐
1 Week	☐	☐	☐	☐	☐
1 Month	☐	☐	☐	☐	☐

Q7. To what extent did each of the following concerns influence the levels of unhappiness you specified in Question #6?

	Not at all	To a minor extent	To a moderate extent	To a major extent
Financial cost	☐	☐	☐	☐
Time or effort to meet household needs	☐	☐	☐	☐
Physical health effects	☐	☐	☐	☐
Stress	☐	☐	☐	☐

Q8. We will now ask about your household's willingness to pay to have access to electricity [water] during an emergency. Imagine that there is a backup service that can be used in case of an electricity [water] outage. This service will cover your household's need for electricity [water] during the length of the outage, which could be **1 DAY, 3 DAYS, 1 WEEK, or 1 MONTH**.

You will only pay for this backup service if an outage caused by an emergency actually occurs. If you choose not to pay for this service, your household will experience the lack of electricity [water].

How much would your household be willing to pay for this backup service during an outage that lasts:

a) 1 Day ☐ Nothing ☐ Some amount (specify amount) $______

b) 3 Days ☐ Nothing ☐ Some amount (specify amount) $______

c) 1 Week ☐ Nothing ☐ Some amount (specify amount) $______

d) 1 Month ☐ Nothing ☐ Some amount (specify amount) $______

Fig. 3 Questions to solicit information associated with hypothetical future outages

power outage could provide a way to cook, for example, but would not replace the lighting or heating function that electricity often provides. It also might come at a financial cost for the gas and a cost in terms of extra time or inconvenience. Tables 2 and 3 summarize the WTP and unhappiness, respectively, for each electric power and water outage of different durations. Note that 34 very high WTP observations (> \$10,000) were truncated to \$10,000. The change had no practical effect on the model coefficients.

Observations from past and hypothetical future outages are combined in the dataset. Eighty-three percent of observations from past outages are less than one day; whereas hypothetical future outages are approximately evenly split among the four durations from 1 day to 1 month. Combining the past and future thus provides a larger range of durations than either would alone. To check if there were systematic differences between the two types of observations, we looked at the 199 electric power observations and 102 water supply observations that had both a past and future outage observation for the same duration. For those observations, we compared the respondent's WTP associated with the past outage and the WTP associated with the future outage. A two-tail paired two sample *t*-test for means showed no evidence that they were different ($p=0.24$ for electric, $p=0.15$ for water). Similarly, for the unhappiness values, a two-sided Wilcox signed rank test showed no evidence of a difference between past and future assessments for water ($p=0.88$), although it did for electric. For electric outages, people tended to assess a higher unhappiness for past one-day outages than for a future outage of the same duration, but a lower unhappiness for past 30-day outages than for a hypothetical future outage of the same duration.

Table 2 Summary of WTP, y_{wtp}, data, by infrastructure type and outage duration

	Electric power					Water supply				
Outage duration	Total responses	Num. $0	Mean[a] ($)	Median[a] ($)	St. dev[a] ($)	Total responses	Num. $0	Mean[a] ($)	Median[a] ($)	St. dev[a] ($)
< 1 h	249	202	281	100	604	68	49	199	75	273
1 h	549	417	553	100	1621	223	190	514	100	1623
12 h	283	178	323	75	1110	120	74	281	95	660
1 day	1723	1253	237	40	1014	1663	1288	125	25	617
3 days	1640	940	219	50	831	1624	1006	197	45	875
1 week	1601	704	301	100	1027	1588	755	222	60	847
1 month	1601	647	536	150	1388	1594	682	423	100	1220
All	7646	4341	350	100	1085	6880	4044	280	75	874

[a]Mean, median, and standard deviation are computed without $0 responses included

Table 3 Number of responses for each degree of unhappiness, y_{un}, by infrastructure type and outage duration

Outage duration	Electric power					Water supply				
	Not unhappy	Slightly unhappy	Moderately unhappy	Very unhappy	Extremely unhappy	Not unhappy	Slightly unhappy	Moderately unhappy	Very unhappy	Extremely unhappy
< 1 h	53	103	56	31	11	15	28	14	8	4
1 h	50	222	188	73	24	39	81	58	33	13
12 h	15	75	93	63	40	6	25	47	27	17
1 day	467	685	349	158	81	460	669	322	142	85
3 days	120	485	634	292	134	134	460	633	255	163
1 week	87	123	416	620	383	78	137	443	597	364
1 month	87	73	145	300	1026	64	72	175	310	1004
All	879	1766	1881	1537	1699	796	1472	1692	1372	1650
All (%)	11.3	22.8	24.2	19.8	21.9	11.4	21.1	24.2	19.7	23.6

4.3 Other explanatory variables

The explanatory variables, selected based on the literature on service interruptions, emergency preparedness, and risk perception (Moreno and Shaw 2019, Dargin and Mostafavi 2020, Heidenstrøm 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 ($x_{e.heat}$, $x_{e.dev}$, $x_{e.work}$, $x_{w.dev}$, $x_{e.work}$), (2) risk perception and past experience in emergencies ($x_{l.emer}$, $x_{w.emer}$, $x_{n.emer}$, x_{prep}), (3) social cohesion ($x_{neighbor}$), and (4) socio-demographics (all other variables). Tables 4 and 5 summarize the descriptive statistics and hypothesized effects for the categorical and continuous variables, respectively. Note that while there were 1,615 respondents as summarized in Tables 4 and 5, since each responded to up to 10 outage scenarios, the number of observations in Tables 2 and 3 are approximately nine times that (14,744 for WTP and 14,522 for unhappiness).

Respondents were asked "In what ways does your household regularly use electricity at your place of residence? (Select all that apply)" Of the ten choices—House heating, house cooling, lighting, cooking and food storage, communications, electronics, washing, medical devices, work and business, or other—to reduce model size, binary variables were included only for heating, medical devices, and work/business ($x_{e.heat}$, $x_{e.dev}$, $x_{e.work}$), as they were hypothesized to be most important. The same question was asked with "water" instead of "electricity" and the ten choices drinking, bathing, cooking, washing, flushing the toilet, medical devices, work and business, swimming pool or hot tub, outdoor uses (lawn, garden), and other. Variables were included only for medical devices and work/business ($x_{w.dev}$, $x_{w.work}$).

To elicit risk perception and past experience in emergencies, respondents were asked several questions. 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 for parsimony was coded as a binary variable ($x_{l.emer}$). Similarly, although there were four options to the question "How worried are you about the potential threat of you and your household being impacted by emergencies in the next five years?" it was coded as binary ($x_{w.emer}$) (Table 4). The negative emergency variable ($x_{n.emer}$) was obtained from the question "Have you ever experienced emergencies that caused some negative impact on your life? (Yes or No)". The Preparation (x_{prep}) variable was coded as the number of preparation-based activities respondents took out of 12 possible activities—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 non-perishable food and snacks, storing first aid supplies, storing flashlights, and storing a battery-operated radio. Respondents were asked specifically "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."

With a particular interest in how social connectedness plays into the ability to adapt to or to prepare for outages/disruptions, 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: 920), (2) People in this neighborhood know each other well, (3) "People in this neighborhood can be trusted" (Sampson et al. 1997: 920), (4) People in this neighborhood participate in neighborhood organizations, and (5) "My neighborhood is a safe place" (Merrin et al. 2015: 527)." The response choices were Strongly disagree, Disagree, Agree, and Strongly agree. To create the composite neighbor connectedness variable, values 1 to 4 were assigned to each response choice respectively, answers

Table 4 Number of respondents associated with each level of categorical variables

Variable	Description	Hypoth. effect[b]	Levels	Num. respondents
x_{type}	Infrastructure service type	Unclear	0: Electric	1615
			1: Water	1615
$x_{e.heat}$	Use electricity for heat	Positive	0: No	801
			1: Yes	814
$x_{e.dev}$	Use electricity for medical devices	Positive	0: No	1474
			1: Yes	141
$x_{e.work}$	Use electricity for work	Positive	0: No	1205
			1: Yes	410
$x_{w.dev}$	Use water for medical devices	Positive	0: No	1520
			1: Yes	95
$x_{w.work}$	Use water for work	Positive	0: No	1483
			1: Yes	132
$x_{l.emer}$	Perceived likelihood of emergency in next 5 years	Positive	0: Very unlikely, unlikely, not sure	515
			1: Likely or very likely	1100
$x_{w.emer}$	Worry about emergency in next 5 years	Positive	0: Not at all or slightly worried	885
			1: Moderately or extremely worried	730
x_{n_emer}	Has experienced a negative emergency	Positive	0: Have not had negative experience	1134
			1: Has had a negative experience	481
$x_{neighbor}$	Feels connection to neighborhood	Unclear	0: Does not feel connected	572
			1: Feels connected	1043
x_{gen}	Gender	Positive	0: Female	838
			1: Male	769
			2: Other	8
x_{race}	Race	Unclear	0: White	428
			1: Hispanic	802
			2: Black	131
			3: Asian	223
			4: Other	31
x_{edu}	Education	Unclear	0: < 4-year degree	1155
			1: 4-year degree +	460

Table 4 (continued)

Variable	Description	Hypoth. effect[b]	Levels	Num. respondents
x_{child}	Children (< 18 yrs) live in household	Positive	0: No 1: Yes	918 697
x_{elder}	Elders (65 + yrs) live in household	Negative	0: No 1: Yes	1176 439
x_{pets}	Pets live in household	Positive	0: No 1: Yes	612 1003
$x_{med.c}$	Anyone with a medical condition in household	Positive	0: No 1: Yes	1167 448
$x_{med.e}$	Anyone in household rely on medical equipment	Positive	0: No 1: Yes	1426 189
x_{own}	Homeownership	Positive	0: Do not own 1: Own	788 827
x_{house}	House type	Negative	0: Single-family, duplex, townhome 1: Apartment 2: Other	1061 492 62
x_{employ}	Employment status	Positive	0: Not traditionally employed 1: Employed full-time or part-time	720 895
$x_{marital}$	Marital status	Positive	0: Not married 1: Married	928 687

[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.

[b]Positive means increase in variable is associated with an increase in WTP or probability of being unhappier

Table 5 Descriptive statistics for continuous variables

Variable	Description (unit)	Hypothesized effect[a]	Num. responses	Mean	Standard deviation
x_{age}	Age (years)	Negative	1615	40.96	16.40
x_{inc}	Income[b] ($1000 s)	Positive	1615	77.47	65.33
x_{prep}	Preparation[c]	Unclear	1615	7.01	3.38

[a]Positive means increase in variable is associated with an increase in WTP or unhappiness

[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 $15 k ($7.5 k), $15 k–$35 k ($25 k), $35 k–$50 k ($42.5 k), $50 k–$75 k ($62.5 k), $75 k–$100 k ($87.5 k), $100 k–$150 k ($125 k), $150 k–$250 k ($200 k), and more than $250 k ($300 k)

[c]Preparation is a continuous value from 0 to 12

for the five statements were averaged, and $x_{neighbor}$ was coded as 0 for Does not feel connected ($\leq$2.5), and 1 for Feels connected (>2.5).

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 coded as binary with Unemployed, Student, Homemaker, Retired, Unable to work combined into Not traditionally employed. To capture possible medical reliance on infrastructure services, respondents were asked "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 (adapted from American Community Survey 2020). Respondents were also asked " 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 $x_{med.c}$ and $x_{med.e}$ were coded as binary variables.

5 Models

5.1 Willingness to pay (WTP) model

The data used in the willingness to pay (WTP) analysis are structured as repeated measures data in that within one survey each respondent is asked multiple WTP questions that vary by condition (i.e., outage type/duration). In particular, there are up to ten choice occasions (and WTP responses) for each respondent, one past experience with an associated outage duration, and four hypothetical future experiences with outage durations of one day, three days, one week, and one month for electric power, and the same for water supply. In the terminology of Bell et al. (2019), the observations have two levels. Level 1 is the choice occasion t (i.e., the question distinguished by the outage type and duration referenced); Level 2 is the individual respondent associated with a group of level 1 observations. We use a random effects within-between (REWB) regression model to capture the heterogeneity at both levels (Bell et al. 2019; Dieleman and Templin 2014). "Within" effects occur at level 1 and "between" effects occur at level 2.

In this analysis, we are most interested in within-effects, i.e., the effect of outage duration, on WTP. This general structure allows the possibility that a response variable can be related to predictors at different levels and the relationships are not always the same, as in the case in which higher-income U.S. states tend to elect more Democratic politicians, but within states, higher-income individuals tend to support Republication politicians more (Gelman 2008).

Equation 1 presents the REWB model specification (Bell et al. 2019; Lüdecke et al. 2021), where y_{it} is ln (WTP + 1), with the log transform included to ensure WTP remains nonnegative, and one is added to ensure it is defined at WTP = 0.

$$y_{it} = \mu + \beta_{1W}\left(x_{it} - \overline{x}_i\right) + \beta_{2B}\overline{x}_i + \vec{z}_i^T\vec{\beta}_3 + v_{i0} + v_{i1}\left(x_{it} - \overline{x}_i\right) + \epsilon_{it0} \tag{1}$$

On the right side, μ is a constant; x_{it} is the level 1 explanatory variable (outage duration) for individual i in choice occasion t; and $\vec{z}_i$ is a vector of level 2 explanatory variables that vary by individual i but not choice occasion t (e.g., respondent income). The coefficients β_{1W} and β_{2B} represent the average within- and between-effects of outage duration, x_{it}, respectively; $\vec{\beta}_3$ represents the vector of effects of the individual-specific variables $\vec{z}_i$.

There are three random components in the model as well. The v_{i0} and v_{i1} are level 2 random effects representing randomness in the intercept and within slope, respectively. Together they allow heterogeneity in the within-effect of x_{it} across individuals. That is, it allows the intercept and slope defining the relationship between ln (WTP + 1) and outage duration to vary with individual. We assume they are drawn from a bivariate Normal distribution (Eq. 2). The ϵ_{it0} are the level 1 residuals, assumed to be Normally distributed. The models were all fitted in R (R Core Team 2021) using the {lme4} package (Bates et al. 2015).

$$\begin{bmatrix} v_{i0} \\ v_{i1} \end{bmatrix} \sim N\left(0, \begin{bmatrix} \sigma_{v0}^2 & \\ \sigma_{v01} & \sigma_{v1}^2 \end{bmatrix}\right) \tag{2}$$

5.2 Unhappiness model

Unhappiness, y_{un}, is measured on an ordinal scale, meaning the order of the levels is important but the difference between levels is not necessarily constant. Thus, we use a type of ordered logit model to represent its relationship to the explanatory variables. The structure of the data is otherwise the same as that used in the WTP model, and therefore we retain the random effects within-between (REWB) representation here. Specifically, the ordinal response $Y_{it,}$ takes on a value of k when individual i (level 2 units) in choice occasion t (level 1 units) falls into the k^{th} ordered category, where $k = 1, \ldots, K$. The probability that individual i in choice occasion t is in category k is p_{itk}, and the cumulative probability is $P\left(Y_{it} \le k\right) = \sum_{l=1}^{k} p_{itl}$. The function that links the probability to the linear predictor is the logit link (Eq. 3) and the cumulative probability is as in Eq. 4:

$$\log\left(\frac{P\left(Y_{it} \le k\right)}{1 - P\left(Y_{it} \le k\right)}\right) = \alpha_k - \left(\vec{x}_{it}^T\vec{\beta} + \vec{w}_{it}^T\vec{\theta}_i\right) \tag{3}$$

$$P\left(Y_{it} \le k\right) = \frac{\exp\left(\alpha_k - \left(\vec{x}_{it}^T\vec{\beta} + \vec{w}_{it}^T\vec{\theta}_i\right)\right)}{1 + \exp\left(\alpha_k - \left(\vec{x}_{it}^T\vec{\beta} + \vec{w}_{it}^T\vec{\theta}_i\right)\right)} \tag{4}$$

where the thresholds separating the k categories are $-\infty = \alpha_0 < \alpha_1 < \cdots < \alpha_{K-1} < \alpha_K = +\infty$; $\vec{x}_{it}$ is the covariate vector; $\vec{\beta}$ is the vector of regression parameters; $\vec{w}_{it}$ is the design vector for the r random effects; and $\vec{\theta}_i$ is the vector of unknown random effects for individual i. The distribution of random effects is assumed to be multivariate normal. In particular, $\vec{x}_{it}^T\vec{\beta} + \vec{w}_{it}^T\vec{\theta}_i = \beta_{1W}\left(x_{it} - \bar{x}_i\right) + \beta_{2B}\bar{x}_i + \vec{z}_i^T\vec{\beta}_3 + \nu_{i0} + \nu_{i1}\left(x_{it} - \bar{x}_i\right)$. The models were fitted in R (R Core Team 2021) using the {mixor} package (Archer et al. 2015; Hedeker and Gibbons 1996).

6 Results

6.1 Final models

The WTP and unhappiness models were both fitted using all the explanatory variables in Tables 4 and 5, as well as outage duration in days ($x_{dur,w}$, $x_{dur,b}$) (Models W1 and U1, Appendix). Using stepwise elimination, variables that were not statistically significant at $\alpha = 0.1$ were removed (Models W2 and U2, Table 6). Since this data is repeated measures data with repeated observations for one individual, the between-effect is meaningless and the REWB formulation is more informative (Ludecke et al. 2021). The marginal and conditional R^2 values for the WTP models describe the proportion of total variance explained through fixed effects and through both fixed and random effects, respectively (Nakagawa and Shielzeth 2013). They suggest that a lot of the variability is in the random effects (0.63 is almost six times 0.11). Comparing the two WTP models and the two unhappiness models suggests that removing the variables that are not statistically significant ($\alpha = 0.1$) had almost no effect on the overall fit. Thus, for simplicity, in the following discussions we focus on results from the reduced models, W2 and U2.

The average marginal effects (AME) were computed for each explanatory variable since they are more easily interpreted than coefficients. The marginal effect is defined as the change in the WTP (or probability of being at least moderately unhappy) 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).

To test if the more complex models that include within and between separation and with random slopes are necessary, we fitted versions of W2 and U2 (1) without the within-between separation (i.e., a random effects model as in Bell et al. 2019, Eq. 4), and (2) with the within-between separation but without the random slope (as in Bell et al. 2019, Eq. 2). Likelihood ratio tests confirmed that the REWB models with random slopes are most appropriate ($p < 0.01$ for all tests). Combining the electric power and water data into a single WTP model and a single Unhappiness model streamlines the analysis and allows more efficient use of the data; however, it assumes that the effects of the explanatory variables are the same for both infrastructure system types. To check that assumption, models were fitted separately for electric power and water supply. The model R^2 values, and coefficient estimates, signs, and p-values were similar in both cases, and would not change the

Table 6 Final WTP and unhappiness models

Variable	WTP, W2			Unhappiness, U2		
	β	p-value	AME[a]	β[b]	p-value	AME[a]
Intercept	0.36	0.278		3.56	<0.001	
Outage duration within, $x_{dur,w}$	0.059	<0.001	7.06	0.37	<0.001	0.0518
Outage duration between, $x_{dur,b}$	0.12	<0.001	8.72	0.14	0.0054	0.0198
Infrastructure type, x_{type}	−0.25	<0.001	−16.74	−0.09	<0.001	−0.0138
Use electricity for med. devices, $x_{e.dev}$	0.30	0.029	22.33			
Use water for work, $x_{w.work}$				0.43	0.005	0.0611
Likelihood of emergency, $x_{l.emer}$	0.20	0.017	12.67			
Worry of emergency, $x_{w.emer}$				0.67	<0.001	0.0984
Negative emerg. experience, x_{n_emer}	0.38	<0.001	26.99			
Preparation, x_{prep}				−0.022	0.108	−0.0032
Neighborhood connection, x_{neigh}	0.19	0.023	11.67			
Elders in household, x_{elders}				−0.29	0.013	−0.0423
Pets in household, x_{pets}	0.23	0.004	14.64			
Has medical condition, $x_{med.c}$				0.43	<0.001	0.0622
Marital status, $x_{marital}$	0.39	<0.001	25.92	0.21	0.034	0.0302
Age, x_{age}	−0.0081	0.001	−0.53			
Income ($1000 s), x_{inc}	0.0015	0.011	0.10	0.002	0.009	0.0003
Intercept,σ^2_{v0}		2.499			10.298	
Outage duration within,σ^2_{v1}		0.0032			0.103	
Intercept-Outage duration within,σ_{v01}		0.510			0.884	
Threshold 1,α_1				−3.558	<0.001	
Threshold 2,α_2				−1.342	0.006	
Threshold 3,α_3				0.715	0.145	
Threshold 4,α_4				3.256	<0.001	
Conditional R^2		0.63				
Marginal R^2		0.11				
AIC		57,193.5			−17,664.2	

[a]AME is average marginal effect

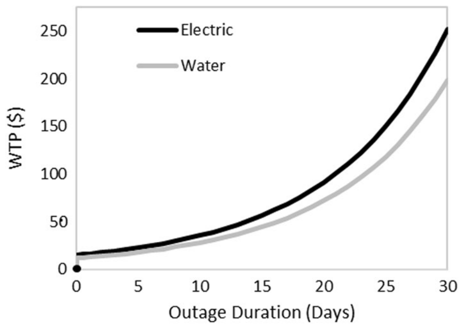
[b]Beta values in the unhappiness model, U2, are those from Eq. 3 that computes log-odds

conclusions herein. Plotting the coefficients for electric power vs. those for water indicated high correlation ($R^2=0.96$ for WTP, $R^2=0.99$ for Unhappiness).

6.2 Effect of infrastructure type and outage duration

The first Research Question asks: *How do household impacts vary with infrastructure system type and outage duration?* The *Infrastructure type*, x_{type}, variable is highly significant ($p<0.001$) and negative in both W2 and U2, suggesting that all things being equal, electric power interruptions cause more severe household impacts than water supply interruptions. The WTP would be $17 more and the probability of at least moderate unhappiness would be 0.014 higher if a service interruption was electric power instead of water.

Fig. 4 WTP vs. outage duration for electric power and water supply



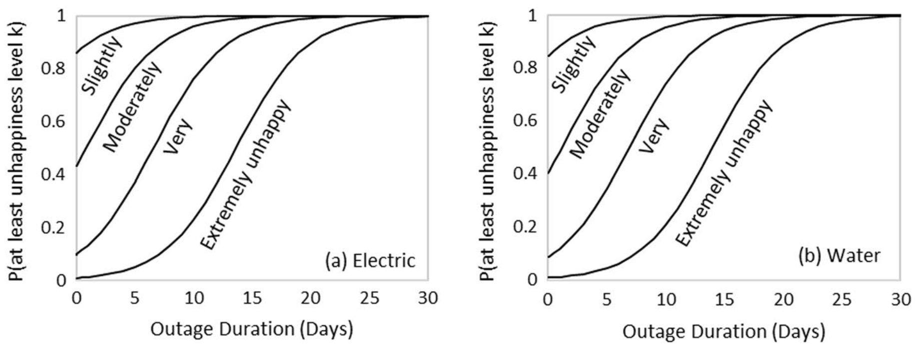


Fig. 5 Probability of at least each unhappiness level k versus outage duration for **a** electric power and **b** water supply

The within-effect of outage duration, $x_{dur,w}$, is also highly significant ($p<0.001$) and positive in both W2 and U2, indicating that outage duration is important in determining household impacts, with longer durations leading to greater impacts. The marginal effects suggest that on average, for each individual, increasing the outage duration by a day results in a willingness to pay $7.06 larger and the probability of at least moderate unhappiness is 0.05 higher. This finding is consistent with the hypothesized effect and with Dargin and Mostafavi (2020), which concluded that as households experienced more days of power outage, they experience more hardship.

Figures 4 and 5 offer another way to examine the effect of outage duration on household impacts of service interruption. To generate a point on the electric power curve in Fig. 4 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 WTP (including random effects at their means), and took the average over all observations. We generated the curve by repeating the process for multiple specified outage duration values x_{dur}. A similar process was followed to develop Fig. 5 but instead of computing WTP we computed the probability of each unhappiness level k. The water supply curves were computed similarly.

As expected, the WTP and unhappiness increase as outage durations increase. The average WTP ranges from $15 ($12) to avoid a one-hour outage to $252 ($199) to avoid a 30-day electric (water) outage. The probability of being at least moderately unhappy is 0.43 (0.40) for a 1-hour electric (water) outage to 1.0 for a 30-day outage. It is important to remember, however that there is quite a bit of variability across the population.

As noted in Petersen et al. (2020), some people are willing to accept at least some service interruption. Considering an outage of one day or less, for electric power and water supply, respectively, 73% and 77% of respondents said they would not be willing to pay anything to avoid it (WTP = \$0), and 21% and 25% would not be unhappy (Tables 2 and 3). For a 7-day outage, for electric power and water supply, respectively, 44% and 47% indicated a WTP of \$0, and 5% indicated they would not be unhappy. The large differences between WTP = 0 and not unhappy highlight the difference between these two measures of household impact. While only one in four would not be unhappy with a 1-day outage, another two in four would be at least slightly unhappy but not be willing to pay to avoid the unhappiness. In general, the WTP measure seems less able to distinguish differences at the low end of impact. The empirical cumulative distribution functions for the two measures indicate the percentage of respondents indicating less than or equal to a specified value of WTP (unhappiness), across all outage scenarios for both electric power and water supply (Fig. 6). They indicate that 53% of responses for WTP were \$0. The ratings were more evenly distributed across the five levels of unhappiness.

Note that since 29% of respondents indicated WTP = 0 for all choice situations they faced, we tried a two-part model in which a logit regression is first used to identify who always chose WTP = 0 and who did not; and then a REWB predicts the WTP value for those in the latter group. The model conclusions were very similar, so for simplicity we used the single WTP model in Table 6.

The effect of outage duration is nonlinear with the marginal impact of each day of outage increasing over time. These nonlinear relationships reflect the assumed model formulations and other relationships could be examined in the future. The goodness-of-fit information for the models suggest, however, the assumptions are reasonable. The WTP and unhappiness are slightly higher for electric power than water, but as assumed in the formulation, the effect of outage duration is the same for both. (Note an interaction between $x_{dur,w}$ and x_{type} was not statistically significant when tested ($p > 0.10$) and thus it was excluded.)

The random effects in the models mean that for each individual, there is a different line representing their relationship between ln (WTP + 1) and outage duration. The model W2 has a positive covariance, σ_{v01}, between the intercept and outage duration within-effect random effects. This means that when the intercept is higher (WTP is higher at very small outage duration), then the slope of the outage duration is higher as well. In other words, the marginal increase in WTP per day is higher for those people who have a higher WTP for very small outages.

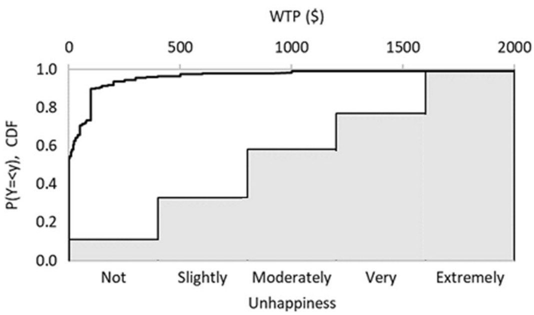


Fig. 6 Empirical cumulative distribution functions for WTP and Unhappiness, considering all past and future hypothetical outage scenarios and both infrastructure system types

6.3 Effects of household characteristics on household impacts

Using the coefficient estimates and marginal effects, we can investigate Research Question 2: *What household characteristics are associated with greater household impacts from electric power and water service interruptions?* Examining the results in Table 6, we consider characteristics related to (1) use of the service, (2) risk perception and past experience in emergencies, (3) social cohesion, and (4) socio-demographics.

The results provide evidence ($p=0.029$) that WTP is on average $22 higher when a household regularly uses electricity on their property for medical devices (e.g., respirators, ventilators, home dialysis), $x_{e.dev}$. Similarly, unhappiness is higher when an individual regularly uses water on their property for work or business, $x_{w.work}$. The analysis did not provide evidence that use of electric power for heat or work/business, or water for medical devices were associated with greater household impacts (Appendix). These explanatory variables describing use of the service provide a way to examine household impacts that is similar to the concept of the needs-based measures described in Sect. 3. Rather than consider broad categories of needs the infrastructure system service helps a household meet (e.g., survival, hygiene, earning income), however, these are defined to possibly vary by household. This analysis is also using the data to empirically test which needs are important in determining household's perceived level of impact in terms of unhappiness.

The risk perception and emergency experience variables were statistically significant. The W2 model suggests that WTP increases with both the perceived likelihood of emergency in the next five years, $x_{l.emer}$, ($p=0.017$) and having experienced a negative emergency, $x_{n.emer}$, ($p<0.001$). The U2 model indicates that unhappiness increases with worry about an emergency in the next five years, $x_{w.emer}$, ($p<0.001$) and possibly decreases with level of preparation, x_{prep} ($p=0.108$). Previous research on the effect of risk perception and emergency experience shows mixed results. Petersen et al. (2020) suggest people with previous disaster experience are more willing to tolerate service reductions, in contrast to the WTP results here. Esmalian et al. (2019) indicates that it is important although the direction of the effect is not specified.

Feeling of connectedness to the neighborhood, x_{neigh}, was statistically significant in the WTP only ($p=0.023$). The model indicates that an individual who feels connected would spend on average $11.67 more to avoid an outage. Social capital is identified as a predictor of tolerance of service outages in Esmalian et al. (2019), but again, the direction of the effect is not specified.

Of the socio-demographic variables tested, there is evidence that higher WTP is associated with higher income, x_{inc} ($p=0.011$), being married, x_{mar} ($p<0.001$), being younger, x_{age} ($p=0.001$), and having pets in the household, x_{pets} ($p=0.004$). For unhappiness, there is similar evidence that increased level of unhappiness is associated with higher income ($p=0.0069$) and being married ($p=0.034$). While there is no evidence that age or presence of pets is statistically significant for unhappiness, having someone with a medical condition in the household, x_{med} ($p<0.001$) is. There was no evidence of a relationship between household impacts and gender, race, education, having children in the household, employment status, homeownership, house type, or having someone in the household who relies on medical equipment (Appendix).

The literature offers somewhat mixed findings related to demographic variables as well. Petersen et al. (2020) indicate that being younger and more educated is associated with increased willingness to tolerate service reductions, but no gender effect was identified. Esmalian et al. (2019) suggests that those with higher income and not a racial minority tolerate longer outages. Coleman et al. (2020) and Dargin and Mostafavi (2020) focus on disparities across populations. The former indicates correlations between tolerance of service interruptions and income, education, race, children, elderly, home type, ownership, and years of residence. The latter finds that race, income, age, and health status are related to well-being impact; however, the conclusions are derived mostly from other infrastructure systems, not electric power or water.

The previous studies vary in the location, infrastructure system type, and emergency type investigated, and specific measures used, possibly leading to differing conclusions. It is also possible that correlations among demographic and other variables account for differences. For example, Petersen et al. (2020) identified education level as important, but it is possible that was actually representing the effect of income, which was not considered.

6.4 Concerns influencing level of unhappiness

To address Research Question 3—*What are the concerns that influence an individual's level of unhappiness associated with service interruptions?*—we asked respondents to identify the extent to which each of four concerns influenced their assessment of their level of unhappiness (Q4 and Q7 described in Sect. 4.2). Note that in asking the questions this way, we obtained responses for past outages and hypothetical future outages, for electric power and for water. Due to survey length limitations and the potential difficulty separating them, no attempt was made to separately identify concerns related to implementing adaptations versus those related to any residual loss of service. The questions also did not require the individual to rank concerns relative to other concerns. As many or as few as desired could be identified.

The results suggest that all four concerns influence level of unhappiness (Fig. 7). Overall, considering both electric power and water, 37%, 59%, 45%, and 63% considered financial, time/effort, health, and stress concerns to at least a moderate extent, respectively. The results indicate, however, that time/effort and stress influenced the level of unhappiness more frequently than financial and health concerns (Fig. 7). This suggests that it is important to consider these harder-to-measure concerns in addition to financial and health effects of service interruptions.

The results also suggest that the extent to which each of the four concerns is considered increases with outage duration. Figure 8 shows the percentage of respondents who said a concern influenced their unhappiness to at least a moderate extent, by outage duration. It indicates that about twice as many respondents identify these concerns as influencing their unhappiness when the outage lasts at least one day.

Comparing the results for electric power vs. water supply suggest little difference in how much each concern was considered. Finally, a key concern is individuals who require electric power and/or water service for medical conditions. Based on chi-squared tests, the

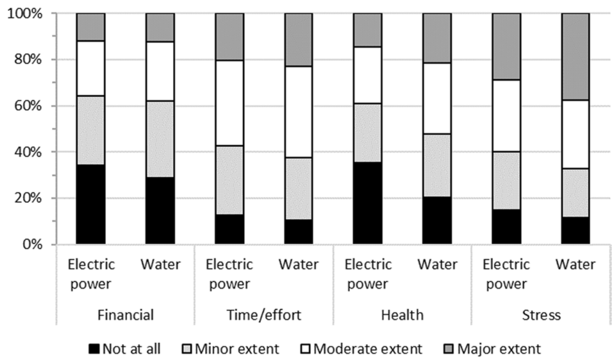


Fig. 7 Extent to which different concerns are considered in assessing level of unhappiness

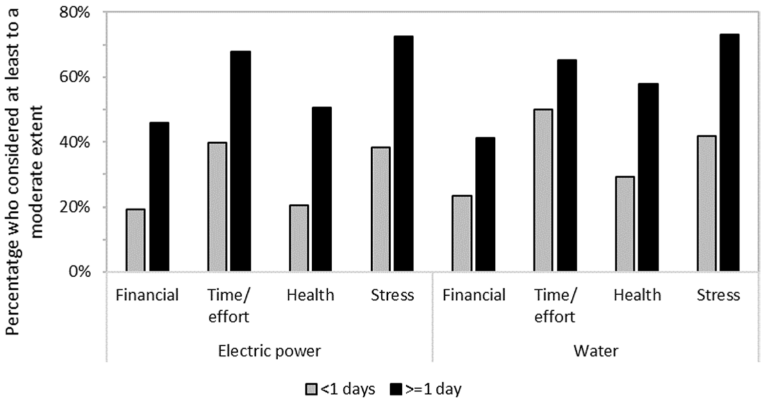


Fig. 8 Percentage of respondents who considered each concern to at least a moderate extent, by outage duration, for each service type and concern

three variables intended to identify these consumers—Medical conditions $x_{med,c}$, Medical equipment $x_{med,e}$, and Use electricity for medical device, $x_{e,dev}$, all had statistically significant relationships with the extent to which health effects were considered (with p-values of 0.003, 0.012, and 0.002, respectively).

7 Conclusions

This paper adds to the small but growing literature that aims to understand the implications of infrastructure system disruptions on households. The commonly used willingness to pay and newly introduced unhappiness metrics both offer ways to measure household impact. The results suggest that household impact as captured by both measures increases nonlinearly with outage duration, and the impact of disruptions in electric power are greater than those in water supply. As outage duration is a typical measure of system interruption, while WTP and unhappiness are measures of societal impact, this suggests a possible nonlinear relationship between system and societal functioning. As a measure, WTP captures the fact that reducing service interruptions involves a cost of some sort and therefore there is an implicit tradeoff (i.e., an inverse relationship) between improved service and expense. As a result, however, it is not a measure only of displeasure caused by a service interruption, but of ability to pay to avoid it as well. To this extent, households view a reduction in service interruption as a normal good and the results show how much a given reduction in service interruption is worth, or its value. Unhappiness is a purer measure of displeasure and provides insight into customer satisfaction. Perhaps for that reason, while WTP is unable to distinguish the effects of outages with shorter durations (all have WTP of $0), unhappiness is better able to capture those effects. While there are outliers up to $10,000 s, most WTP responses are in the range of $100 or less. Unhappiness ratings were distributed relatively evenly across the range from not at all unhappy to extremely unhappy.

Several household characteristics were identified as having a relationship with household impact as measured by WTP and/or unhappiness. These included some related to the way the service is used, in particular if electricity is used for medical devices or water is used for work or business. Perceived likelihood of an emergency, worry about an emergency, past negative experiences with emergencies, lower level of preparation, and less connection to the neighborhood were also associated with increased household impact. Among socio-demographic variables, there was evidence that increased household impact is associated with higher income, being married, being younger, having pets, and having someone with a medical condition in the house. Multiple reasons were reported as contributing substantially to the stated level of unhappiness, including financial, time/effort, health, and stress. All should be considered in future work.

These findings can help infrastructure system operators, emergency managers, and community officials gain more insight into the degree of impact caused by service interruptions, how they depend on outage duration, and how they vary across types of infrastructure systems and residential consumers. This type of information should help guide development of mitigation, response, and restoration activities that can minimize not just service interruption, but household impact.

Naturally the broad outlines are known. Households depend on electricity for heat, light, communications, cooking, and medical appliances, among numerous other functions for work, recreation, and daily living. They depend on water for drinking, hygiene, and cooking. Industries of every description need these services in the conduct of the modern economy. But the impacts of infrastructure service interruptions are not known with any precision, and not to the degree needed to support the development of knowledge about recovery that has been identified by scientists and policymakers as a critical recovery need. While it could generally be supposed that infrastructure service outages would yield negative consequences, an important element needed for theoretical advancement is in establishing the qualitative and quantitative assessments of social impacts.

This paper is founded on a recognition that many systems of critical infrastructure are in need of modernization or are vulnerable to failure in disaster events. Growing scholarship looks at the societal function that infrastructure supports, while other researchers have looked at how people adapt to outages (e.g., Palm 2009). Knowing the “value” of societal function is important in guiding scientists and policymakers in repair or retrofit priorities. Part of that value is the value that people place on reliability, and their level of unhappiness when they cannot meet their accustomed needs. This paper provides both a method for pursuing this knowledge, and a range of values in a large heavily urbanized area. In considering the costs of infrastructure failures, willingness to pay and levels of unhappiness can provide benchmarks to which to relate the costs of needed improvements. The last few years have seen repeated failures in large, well-developed systems. A more complete and nuanced assessment of the costs of those outages is critical for informed investments in future capacity.

There are a number of limitations of the work presented that point the way towards future research and development. Specific model formulations were adopted in this paper, but others could be tested. In particular, it would be valuable to continue to explore the nonlinear form of the relationship between household impacts and outage duration, perhaps using machine learning techniques. The reasons behind unhappiness ratings were only examined in aggregate form, considering four types of considerations—financial, time/effort, health, and stress. Future work could examine the reasons in more depth by defining them more specifically, investigating the circumstances under which each are most important, and examining their specific causes (e.g., what specifically causes stress). Similar studies that consider more types of infrastructure systems, types of events (e.g., hurricanes), geographic locations, and possible measures of household impact, will be important to develop the relationship between infrastructure system interruptions and household impacts.

Appendix

See Table 7.

Table 7 WTP and unhappiness models with all variables included

Variable	WTP, W1			Unhappiness, U1		
	β	p-value	AME	β[a]	p-value	AME
Intercept	0.41	0.268	–	3.569	< 0.001	–
Outage duration within, $x_{dur,w}$	0.059	< 0.001	7.02	0.369	< 0.001	0.0515
Outage duration between, $x_{dur,w}$	0.13	< 0.001	9.05	0.164	0.003	0.0234
Infrastructure type, x_{type}	− 0.25	< 0.001	− 16.73	− 0.091	< 0.001	− 0.0133
Use electricity for heat, $x_{e.heat}$	0.018	0.816	1.21	0.032	0.742	0.0047
Use electricity for med. devices, $x_{e.dev}$	0.26	0.113	18.81	0.290	0.140	0.0411
Use electricity for work, $x_{e.work}$	0.101	0.304	6.78	0.034	0.785	0.0050
Use water for med. devices, $x_{w.dev}$	− 0.16	0.415	− 9.66	0.213	0.352	0.0304
Use water for work, $x_{w.work}$	0.09	0.586	5.89	0.286	0.122	0.0406
Likelihood of emergency, $x_{l.emer}$	0.19	0.034	11.89	− 0.076	0.493	− 0.0110
Worry of emergency, $x_{w.emer}$	0.034	0.678	2.28	0.675	< 0.001	0.0986
Negative emerg. experience, x_{n_emer}	0.35	< 0.001	24.95	0.208	0.064	0.0300
Preparation, x_{prep}	0.0048	0.686	0.32	− 0.024	0.093	− 0.0035
Neighborhood connection, x_{neigh}	0.15	0.075	9.49	− 0.021	0.842	− 0.0030
Male, x_{gen1}	− 0.077	0.344	− 5.07	0.005	0.958	0.0008
Other gender, x_{gen2}	− 0.109	0.842	− 7.09	0.201	0.777	0.0287
Hispanic, x_{race1}	− 0.12	0.228	− 8.17	− 0.191	0.140	− 0.0281
Black, x_{race2}	0.26	0.096	20.80	0.341	0.065	0.0473
Asian, x_{race3}	− 0.09	0.473	− 6.21	0.171	0.294	0.0243
Other, x_{race4}	− 0.48	0.100	− 26.52	− 0.136	0.721	− 0.0199
Education, x_{edu}	0.16	0.087	10.67	0.085	0.482	0.0123
Children in household, x_{child}	0.11	0.219	7.15	0.034	0.761	0.0049
Elders in household, x_{elders}	0.021	0.833	1.38	− 0.274	0.032	− 0.0403
Pets in household, x_{pets}	0.23	0.007	14.32	0.117	0.253	0.0170
Has medical condition, $x_{med.c}$	0.16	0.093	10.82	0.466	< 0.001	0.0664
Rely on medical equipment, $x_{med.e}$	0.034	0.803	2.27	0.217	0.22	0.0318
Homeownership, x_{own}	− 0.17	0.082	− 11.40	0.080	0.498	0.0116
Apartment, x_{house1}	− 0.17	0.074	− 10.90	0.024	0.844	0.0035
Other home type, x_{house2}	− 0.44	0.034	− 24.21	− 0.151	0.53	− 0.0222
Employment status, x_{employ}	− 0.065	0.441	− 4.31	0.081	0.451	0.0118
Marital status, $x_{marital}$	0.36	< 0.001	23.98	0.206	0.062	0.0299
Age, x_{age}	− 0.0071	0.024	− 0.47	-0.003	0.424	− 0.0005
Income ($1000 s), x_{inc}	0.0014	0.046	0.093	0.001	0.339	0.0001
Intercept,σ^2_{v0}		2.481			10.10	
Outage duration within,σ^2_{v1}		0.0032			0.103	
Intercept-Outage duration within,σ_{v01}		0.510			0.877	
Threshold 1,α_1				− 3.569	< 0.001	
Threshold 2,α_2				− 1.350	0.025	
Threshold 3,α_3				0.705	0.243	
Threshold 4,α_4				3.242	< 0.001	
Conditional R^2		0.627				
Marginal R^2		0.113				
AIC		56,955.7			− 17,582.7	

[a]The beta values in the unhappiness model, U1, are those from Eq. 3 that computes log-odds

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Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data availability Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability R was used for analysis of the data in this article (R Core Team 2021).

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