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Do notifications affect households' willingness to pay to avoid power outages? Evidence from an experimental stated-preference survey in California

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ABSTRACT

How much should electric utilities pay to maintain a reliable electricity system? This paper describes an open-ended stated-preference experiment that generates estimates for how advanced notification impacts household willingness-to-pay (WTP) to avoid outages. We find positive and statistically significant WTP to avoid power outages of $10/kWh, consistent with the expectation that outages are costly to the residential sector. We find notification reduces the WTP, but the effects are not statistically significant. There is limited evidence that these results vary by income and wealth levels. Back-up power ownership is positively correlated with respondents' WTP to avoid outages.

1. Introduction and literature review

Electric power outages are costly and negatively impact individuals, businesses, and governments. For individuals, outages result in the loss of food, access to leisure activities, and potentially vital health services such as breathing machines. For businesses, electricity is often critical to serving customers and earning revenues while governments rely on electricity to provide vital public services. Balancing the benefits of avoiding power outages with the cost of electric grid investments is a long-studied and fundamental trade-off in energy economics and electricity system design (Crew and Kleindorfer, 1978; Munasinghe and Gellerson, 1979; Telson, 1975). In the U.S., utility business practice and regulatory decisions have resulted in a low frequency of power outages, with less than 5 h of outage per customer in recent years (Arlet, 2017; EIA, 2020; Spees et al., 2013).

Regulators and utilities often make use of a measure of the marginal damages from outages known as the Value of Lost load or "VoLL" (Fig. 1–1) to weigh the cost of increasing grid resilience against the reliability benefits those investments deliver (Gorman, 2022). For example, by comparing the VoLL to the cost of new generation, planners can identify a socially optimal planning reserve margin (Carvallo et al., 2021; Frayer et al., 2013; London Economics, 2013; Pfeifenberger et al., 2013). The VoLL can also be used to optimize investments in electricity networks (Moreno et al., 2020), especially distribution systems, where the majority of network-related power outages occur in the U.S. (Eto et al., 2019).[1] The VoLL is also a key parameter in decisions to manage, upgrade, and/or shut-off electric transmission and distribution infrastructure during extreme weather events (Fenrick and Getachew, 2012; Larsen, 2016), and it can clarify investment trade-offs in the face of climate change-induced challenges to grid infrastructure such as wildfire, hurricanes and winter storms (Abatzoglou et al., 2020; Chen et al., 2017). In the past decade, natural disasters such as Hurricane Maria in Puerto Rico, electricity-induced wildfires in California, and Superstorm Sandy in the Northeast has led to increasing calls for grid hardening (Walton, 2017)

Prior studies to estimate the VoLL have either taken a stated

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[1] Past research in the United States found that the distribution network incurs between 92% and 94% of allpower interruptions, a breakdown that has been consistent overtime.

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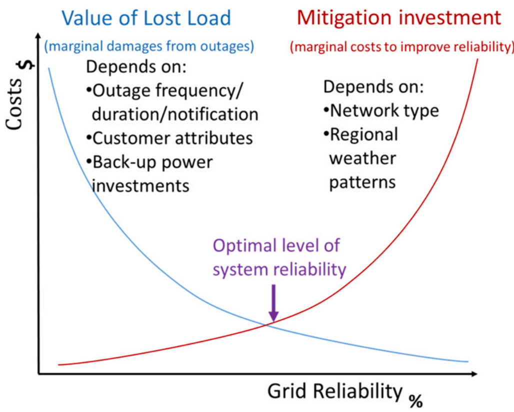

Fig. 1–1. Illustration of Tradeoff between grid investments (red line) and value of lost load (blue line).

preference approach or use production function methods (Caves et al., 1990). These approaches are especially common in high-income countries where experimental research designs with random assignment of reliability outcomes are infeasible due to equity and access concerns in a system which already maintains a high amount of reliability (Fowlie et al., 2018).

In the stated preference approach, households and/or firms are typically asked either how much they would be willing to pay (WTP) to avoid a hypothetical power outage or how much they would have to be paid to accept (WTA) a hypothetical outage. Many of these studies exist for populations in the United States (Baik et al., 2020; Chowdhury et al., 2004; Sullivan et al., 2009), Europe (Abrate et al., 2016; Broberg et al., 2021; Praktiknjo, 2014), and numerous other regions (Alberini et al., 2022) and have estimated a wide VoLL range between $1–25/kWh for private end users of electricity (Schröder and Kuckshinrichs, 2015). This large range is due to a variety of factors including the context (i.e. various countries, different customer types, and differing outage durations) and the study design (Hartman et al., 1991; Hausman, 2012). In contrast, production function methods involve estimating (or, more commonly, calibrating) a representative electricity-using firm's or economy's production function using data on outputs, electricity, and other inputs (Castro et al., 2016; Shipley et al., 1972). One then calculates the implied effect of a power outage by constructing an estimate of output in the absence of power (Munasinghe and Gellerson, 1979; Wolf and Wenzel, 2016). A similar method is used for households, where researchers estimate either a household income production function or a leisure production function (Becker, 1965). Similar to stated preference methods, production function methods have estimated a wide VoLL range between $6–45/kWh for private end users of electricity (Schröder and Kuckshinrichs, 2015).

Outages that affect customers are typically unplanned. However, since 2019, millions of customers in California have been impacted by "Public Safety Power Shutoffs" (PSPSs). These outages occur during extreme fire risk conditions to prevent electricity infrastructure from causing ignitions that lead to destructive wildfires (Wong-Parodi, 2020). For instance, the 2018 Camp fire destroyed the town of Paradise, burned over 18,000 structures, and resulted in 85 deaths (CalFire, 2021), making it the United States' deadliest fire in a century. Because extreme fire risk conditions are forecastable, it is possible to notify customers in advance of a PSPS event. More recently, in 2021, PG&E began implementing an "enhanced power safety shutoff" (EPSS) program that increases the sensitivity of distribution system circuit breakers to ignition-causing incidents such as vegetation contact (PG&E, 2023). Because EPSS events come without advance warning, this program reduced PG&E's ability to notify its customers before wildfire mitigation-related outages occur. However, it is difficult to evaluate the costs and benefits of these programs relative to each other, because little is understood about the value of advance notice and its timing (Caves et al., 1990; Schröder and Kuckshinrichs, 2015; Sullivan et al., 2009). This paper aims to fill this gap.

More broadly, understanding the benefits of advance notice can help decision makers evaluate investments in communications infrastructure and procedures that enable longer lead time decisions. The answer to this question also has important implications beyond direct costs on customers. For example, lack of advance notice may increase a customer's propensity to purchase backup power. This result could undermine environmental policy if outages are sufficiently costly and frequent, leading customers to invest in fossil fueled back-up generators and increasing emissions, noise, and risks of hazards associated with fuel storage (Farquharson et al., 2018; Hwang et al., 2023; King, 2021; Moss and Bilich, 2021).

In this paper we develop an experimental survey to understand how advanced notification of future power outages impacts a customer's VoLL. The experimental open-ended stated-preference survey focuses on consumer behavior and expectation surrounding recent PSPS events in California. We test a hypothesis that customer notifications could reduce the social cost of planned outages in the new context of wildfire risk. Furthermore, we compare survey results for customers with and without backup power. Though such information is commonly studied in low-income contexts (Abdisa, 2018; Jha et al., 2021), it is rare in the literature studying high-income countries. There are several other power outage experiences that could influence respondent WTP that were not explored in our survey. While our study focused on backup ownership and outage notification, other outage contexts like outside weather conditions (i.e. extreme hot or cold during outage) or geographic exposure (i.e. widespread or contained outage) could influence WTP estimation (Gorman, 2022).

While our research focuses on electricity systems, it also relates to the broader literature on the detrimental impact of uncertainty on economic outcomes (Baker et al., 2016; Ben-David et al., 2018; Jackson et al. n.d; Kliesen et al., 2018). Though advance warning technology for natural disasters such as earthquakes, wildfires, and hurricanes is increasingly available (Andrews et al. n.d; DeVries et al., 2018; NAS, 1991; Serna, 2020), we have limited empirical evidence on the benefits of these technologies (Escaleras and Register, 2008; Kellenberg and Mobarak, 2011). Such evidence is critical for determining the optimal level of investment in them, and this paper contributes important knowledge about public investment in early-warning systems. The experiment focuses on wildfires and their interaction with electricity consumption, allowing us to estimate the value of resolving uncertainty in the specific context of household electricity decision making.

Overall, we find positive and statistically significant WTP to avoid power outages. While we show that advanced notice of a power outage reduces the WTP to avoid those power outages, these effects were not statistically significant. The insignificance shows that there was no measurable effect of notification on a consumer's power outage cost within our sample, suggesting that notification may not have a central impact on WTP when compared to other factors. Still, notification did serve to reduce WTP amounts between 10% and 20%. We calculated an average VoLL of $10–14/kWh, within the range of estimates in prior work (Schröder and Kuckshinrichs, 2015). Other key results relate to heterogeneity across household wealth, which was negatively correlated with WTP, a counter intuitive result if one expects that ability to pay to be positively correlated with WTP outcomes. Lastly, we find that back-up power adoption ownership within the sample showed positive correlation with respondents' WTP to avoid outages.

2. Methods

The experimental approach measures the stated VoLL among a randomized sample of California residents age 18+ as selected from the National Opinion Research Center's (NORC's) AmeriSpeak Panel.[2] AmeriSpeak is designed to be representative of the United States household population. U.S. households are randomly selected with a known, non-zero probability from the NORC National Frame as well as address-based sample (ABS) frames, and then recruited by mail, telephone, and by field interviewers face to face. The panel uses sampling strata based on age, race/ethnicity, education, and gender (48 strata in total). The size of the selected sample per sampling stratum is determined by the population distribution for each stratum. In addition, sample selection considers expected differential survey completion rates by demographic groups so that the set of panel members with a completed interview for a study is a representative sample of the target population. If panel household has more than one active adult panel member, only one adult in the household is eligible for selection (random within-household sampling).

The survey was offered in English and Spanish and was administered on the web. Limiting the sample to California should reduce hypothetical bias common to contingent valuation due to the state's recent wildfires and PSPS programs as residents of the state should have more familiarity with the risks of power outages. Importantly, we apply panel base sampling weights provided by NORC that account for non-response. The cumulative response rate accounting for sample recruitment (17%), household retention (75%), and survey completion (21%) was 2.75%. In addition, due to the focus on a California subsample of NORC's AmeriSpeak Panel, we supplemented the sample with respondents from the Lucid's nonprobability online opt-in panel. NORC used their TrueNorth[3] calibration services to explicitly account for potential bias of combining probability and nonprobability-based samples (Cornesse et al., 2020; Ganesh et al., 2017; Yang et al., 2018). TrueNorth is the NORC calibration solution for combining probability and non-probability samples for estimation through small area modeling that leverages data from AmeriSpeak, the American Community Survey, Current Population Survey, and other data sources for improved statistical efficiency. Please see more detail about sampling weights and the TrueNorth in the supplemental information section.

The online interviews were open from Monday, December 20th, 2021 through Monday, January 3rd, 2022. NORC took the following steps to notify and gain the cooperation of invited Panelists for this survey: (1) invitation emails on Monday, December 20th and Tuesday, December 21st, 2021; (2) reminder emails on Thursday, December 23rd, Tuesday, December 28th, 2021, and Sunday, January 2nd, 2022. Panelists were offered the cash equivalent of $2 for completing the survey. Interviewed respondents took 5 min (median) to complete the survey.

The experimental question asks for a respondent's WTP to avoid power outages (VoLL) under different notification scenarios. Specifically, we state that a monthly fee will be added to the respondent's electricity bill every month for the upcoming year (2022). Furthermore, to align with the California PSPS context, we describe that this fee would allow the respondent to avoid two separate, 40-h power outages that would occur randomly during fire season (September through November).[4] Depending on which treatment group the respondent is randomized into, they were told that prior to each outage they would receive either 1) no, 2) 1-day, or 3) 7-day notice. Given a notification window, they then select the monthly fee they would be willing to pay over the entire year to avoid these outages.

Though stated preference methods have a number of limitations (e.g. scope/embedding effects, hypothetical bias, the endowment effect), they also are the only setting with enough flexibility to evaluate identical scenarios that differ only in the advanced notice built into an experimental treatment (Fischhoff, 2005, 1991; Hausman, 2012). Johnson et al. provide useful guidance for stated preference studies that help overcome these challenges (Johnston et al., 2017). In addition to the experimental questions, all respondents answered a set of questions about their prior exposure to and awareness of wildfire-related outages, expectations for future outages, and understanding of power outage defensive investments. These non-experimental questions provide opportunity to explore more detailed heterogeneity among customers.

We assess how the results vary by respondent education, race, home type, home value, household income, and age to understand what equity concerns may exist in policy discussions if only applying an average WTP metric which might vary significantly depending on the population being studied. We conclude the experiment asking respondents how much they pay monthly for electricity. Fig. 2–1 provides a flow diagram illustrating the order of the questions and structure of the experiment. The exact survey instrument deployed can be found in the Supplemental Information.

The null hypothesis is that the level of advanced notification does not affect the WTP to avoid power outages. We used power calculations to find that detecting a 15–20% difference in the VoLL would require a sample size of 1500–2500 observations. In total, we collect responses from 2120 households. Details of these power calculations are provided in the Supplemental Information section.

Eq. 1 estimates the effect of notification on the sample's WTP to avoid power outages. We control for back-up power ownership (i.e. either fossil-fuel generator and/or solar/storage system), which aligns with the stratification strategy. Furthermore, we control for a number of demographic characteristics, including education, race, home type, home value, household income, and respondent age.

$$WTP_i = \alpha + \beta_1 T + \beta_2 X_i + \varphi_b + \varepsilon_i \tag{1}$$

Where,

WTP = WTP for customer i to avoid power outages[5]

T = indication of 0-, 1- or 7-day notice

β_1 = change in WTP for treatment groups

X_i = set of demographic controls

φ_b = fixed effect on stratification by back-up power ownership

ϵ_i = error term

In addition to showing the raw WTP outcome from the survey ($ per month paid 12 times over the year), we also calculate WTP as a % of their reported monthly bill and in $/kWh, based on an estimate of monthly energy consumption. To convert the $/month WTP to $/kWh, we divide the implied annual willingness to pay by an estimate of the energy unserved from 80 h of outage (as specified in the experimental question). To compute the unserved energy from 80 h of outage, we convert each respondent's reported monthly bill into monthly consumption using the Energy Information Agency's 20.45 cents/kWh estimate of the average residential retail price for electricity in California (EIA, 2021),[6] and multiply this amount by 0.11 (80 h as a fraction of an average 730 h month.

[2] Find more information on AmeriSpeak online here: https://www.amerispeak.org/

[3] Find more information on TrueNorth online here: https://amerispeak.norc.org/us/en/amerispeak/our-capabilities/truenorth.html

[4] The specification of duration in these interruptions was based on analysis of the large 2019 PSPS events that occurred in Pacific Gas & Electric's territory, summarized in the following state utility commission dataset: https://www.cpuc.ca.gov/consumer-support/psps/utility-company-psps-reports-post-event-and-post-season

[5] Calculated as either $/month (to get total WTP, multiply by 12 payments given survey question that suggested monthly payments over the entire year), % of monthly bill, or $/kWh

[6] In California, electricity customers do not have one fixed $/kWh electricity price, rather they are on a mix of time-of-use and increasing block pricing rates. We do not know the rate design of the particular respondents, however, and therefore have to calculate a rough estimate of monthly consumption.

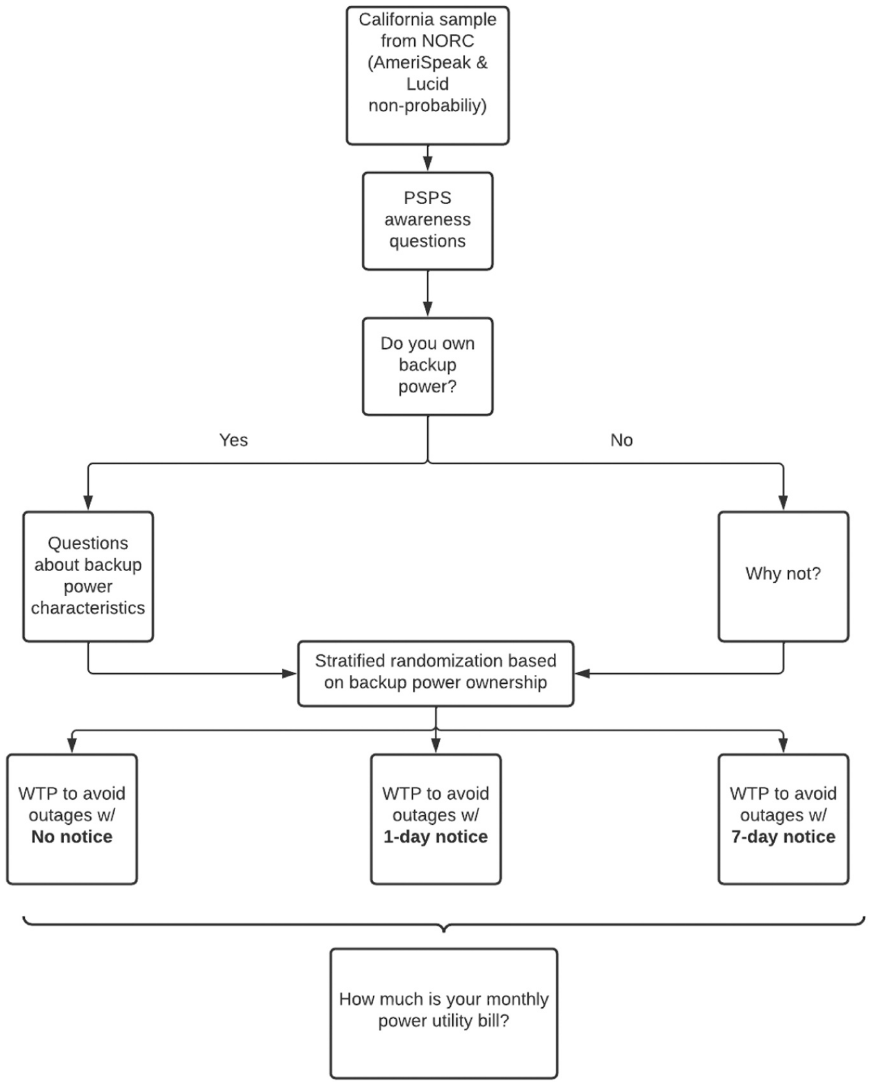

Fig. 2–1. Flow Diagram illustrating experimental design.

3. Results

3.1. Responses to non-experimental survey questions

The first questions of the survey focused on respondent experiences and future expectations for sustained power outage events. We draw three key conclusions from the responses to these questions. First, we find that almost the entirety of the sample is aware of wildfire-related power outages, and 25% experienced one directly. Second, we find that the annual mean expectations for future power outages are relatively low at 12 h per year per respondent, with that number roughly doubling if respondents experienced a sustained power outage over the last three years (i.e. 2018–2021). Finally, we find that while backup power purchases have increased in recent years, low cost mitigation options like using flashlights and candles remain more popular.

Fig. 3–1 summarizes the responses to questions about exposure to historical power outage and expectation for future outages. Almost all of the respondents were aware of the wildfire-related power outage program in California. Of the 2120 total respondents, only 72 indicated that they were unsure about the presence of these shutoffs. At the same time, the majority of respondents did not directly experience a sustained power outage themselves (n = 1368 out of 2120). However, roughly half suggested that someone in their social network (e.g. friends, neighbors, family, coworkers) did experience a sustained power outage.

Roughly 35% of respondents who owned backup power indicated they experienced a sustained power outage over the last 3 years, compared to only 20% of non-backup power owning respondents.

While many of the respondents indicated they experienced a sustained power outage event, they indicated small expected hours of outage in 2022 (bottom left of Fig. 3–1). A majority of respondents expected 0 h of outage hours in 2022. On average, though, respondents expect 12 h of outage with a median response of 3 h. These numbers increase after conditioning on backup power ownership and exposure to outages: backup power owners (35% of the sample) expect 16.5 h (median = 4), and those exposed to prior outages expect an average of 20 h of outages (median = 10). Those who own back-up and experienced prior outages expect an average of 22 h of outages (median = 10). Forty-four percent of respondents expect that these hours will increase in the next five years while 38% expect the outage hours to stay relatively constant. The remaining 18% of respondents expect a decrease in future outage hours.

The next set of non-experimental questions focused on mitigation strategies respondents would take in the case of a power outage event. The left graph in Fig. 3–2 shows that the most common mitigation strategy was the simplest – use of a flashlight and candles – with over 75% of respondents choosing that mitigation strategy. All of the other strategies were chosen by no more than 20% of respondents. The right graphic shows that the majority of respondents did not indicate plans to

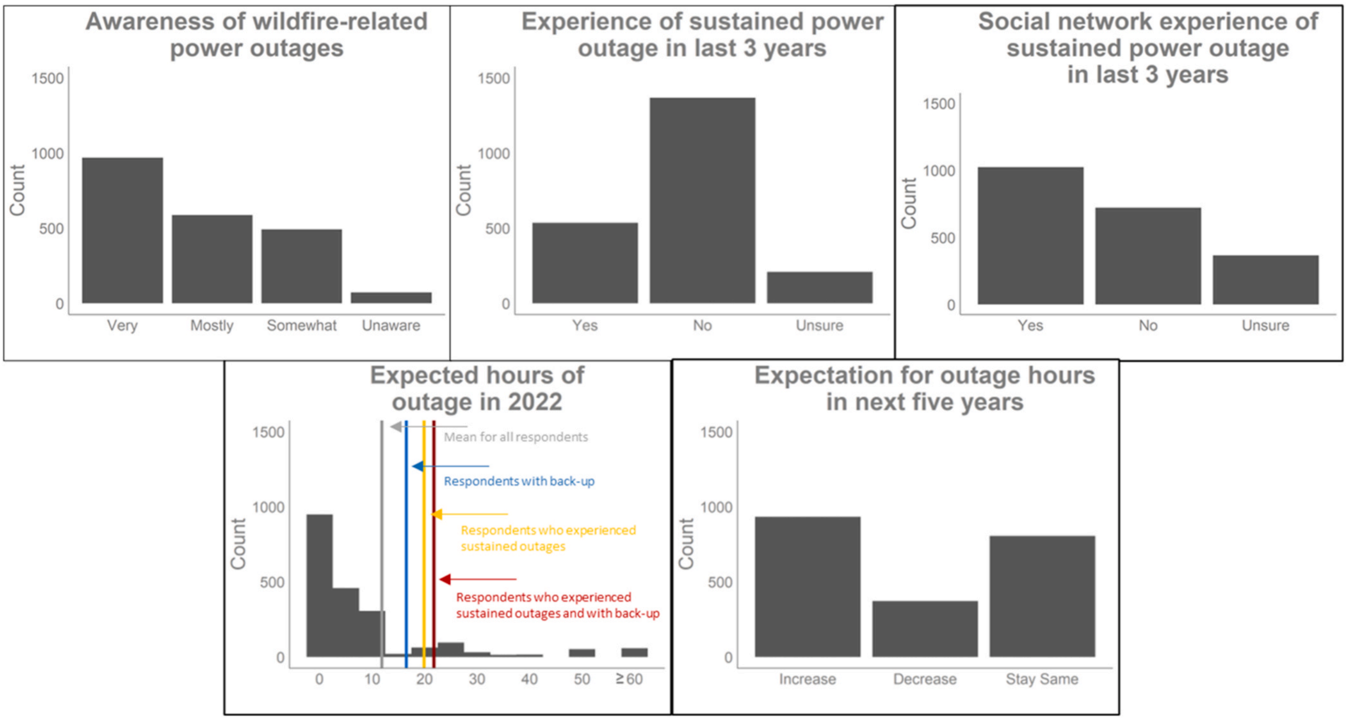

Fig. 3–1. Respondent experiences with sustained power outage events.

purchase backup power in the next 6 months. Such results suggest respondents believe it relatively easy to adapt to the type of outages explored in this study, which did not explicitly focus on extreme weather conditions that might increase the difficulty to adapt to an outage. More physically difficult conditions might influence respondent's response to mitigation strategies and augment the WTP results presented in the next section.

For respondents who owned backup power, Fig. 3–3 shows both when that purchase was made as well as a histogram of the total amount spent on the purchase. There has been a notable increase in backup-power purchases after 2015, predating the experience of PSPS events in California. Most respondents stated that they spent $1000 or less on their system, which is a lower estimate than expected for those that indicate they purchased a solar and/or storage system. Prior work has shown average costs of $4000/kW for solar and $1000/kWh for batteries with typical system sizes of 6 kW and 13 kWh, implying an overall installation cost of $37,000 (Barbose et al., 2021).[7] We also ask individuals who did not own backup power why they made this decision. Fig. 3–4 shares their top 3 reasons: (1) too expensive, (2) they find other mitigation options, and (3) they do not experience significant outages.

3.2. WTP to avoid outages

Overall, we find that respondents had positive and statistically significant WTP to avoid power outages. The WTP did not depend significantly on the advanced notification of the power outage. Respondents who indicated ownership of back-up power had a higher WTP to avoid power outages than non-back-up power owners. Table 3–1 presents summary statistics on the WTP responses. On an annual basis, the full sample has a mean WTP of $941, compared to $597 for households that do not own backup power. These data, however, are quite skewed. Median values for both samples are only $120 per year, suggesting that a small number of our sample has significantly higher WTP (see 95th percentile results in Table 3–1).

Table 3–2 presents the results of the regression on the population. The preferred specification in the regression applies the demographic and backup power controls, statistical weights from NORC,[8] and robust standard errors. These results are shown in column 4 while columns 1–3 show the addition of various components of the preferred specification. We drop 55 of the 2120 respondents who skipped the experimental question. We find that a 1-day or 7-day notification results in a lower WTP by 10–20% but the coefficient is not statistically significant across any of the specifications. Prior research has suggested that notification would allow for preparation and substitution away from electricity during the outage, aligning with the direction the findings. However, the insignificance of the effect suggests that other factors we study (e.g. backup ownership) or factors that other researchers study (e.g. residential vs. industrial and outage duration) may have a more important impact on WTP compared to outage notification. Controlling for prior experience with a wildfire related outage did not impact these results, though the 25% of respondents that experienced an outage prior to the survey did report higher WTP.

The average WTP to avoid power outages was positive and significant, as suggested by the intercept coefficient. Without applying any controls, this coefficient equals $86/month, representing the average WTP for the respondents that received no notice of the power outage event. The heterogeneity across these demographic categories is discussed in the next section.

The backup power ownership row shows the coefficient associated with the fixed effect on backup power ownership. We find that respondents who indicate that they owned backup power reported a statistically significant higher WTP to avoid outages. Respondents who owned generators had a higher WTP than respondents who just owned

[7] One explanation for this low amount could be that subsidies have been offered in California for certain individuals. Alternatively, it could be that respondents were referencing car battery purchases or other cheaper forms of solar/battery solutions rather than rooftop solar and Lithium-ion batteries.

[8] Details about the statistical weights are shared in the second section of the supplemental information. These weights were provided for each survey respondent.

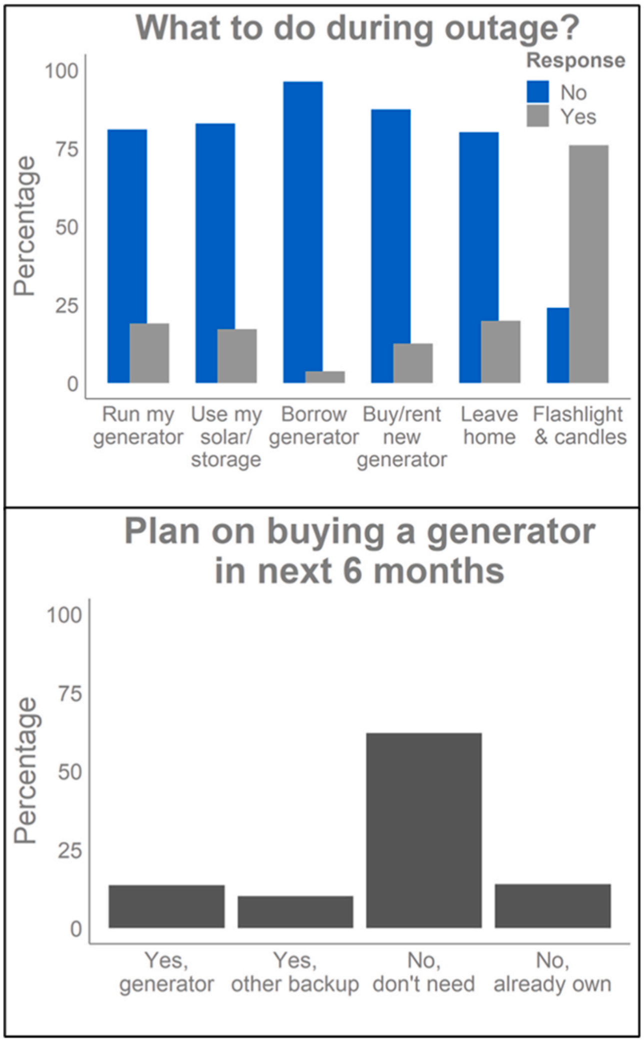

Fig. 3–2. Respondent preferences during backup power experience.

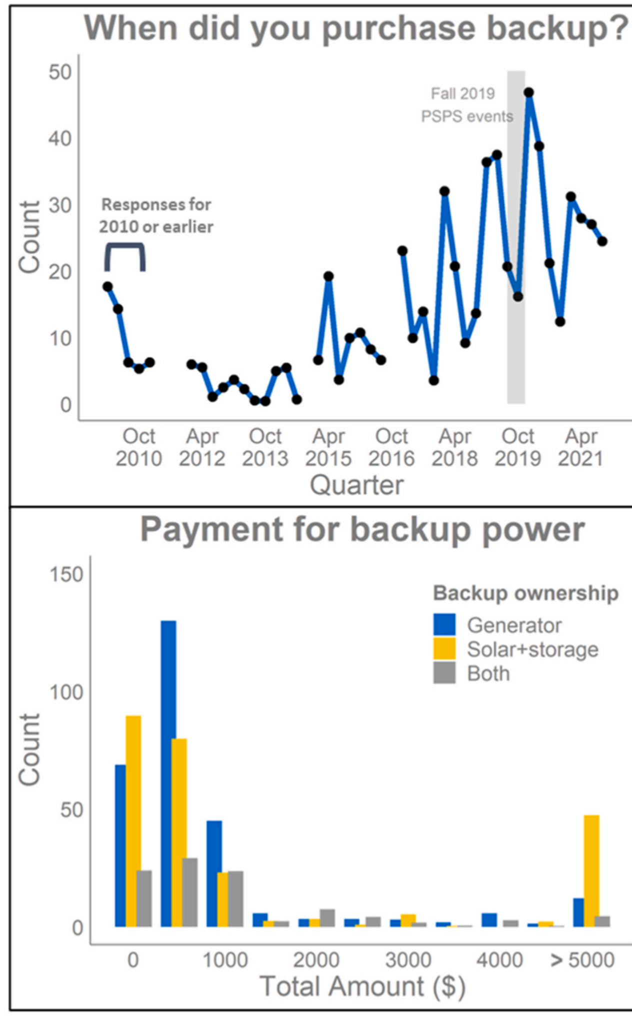

Fig. 3–3. Breakdown of when respondents purchased backup power and how much it cost. Gaps in the left graphic indicate that no backup purchases were made in those quarters.

solar/storage systems, and respondents who indicated ownership of both generators and solar/storage had the highest WTP (see Fig. 3–5). While ownership of backup power mitigates grid outages – which could elicit a lower WTP for grid outages (LaCommare et al., 2018) – we propose three interpretations to explain why backup owners nonetheless reported a higher WTP.

First, generator-owning respondents may have been reporting their WTP to avoid outages assuming both the grid and their backup supply failed (scenario (a) in Fig. 3–6). Their higher WTP, therefore, would align with their decision to purchase backup power. Alternatively these respondents may have purchased backup power technologies that cannot fulfill their entire electricity demand during outage events, and they reported WTP for their residual lost load (scenario (b) in Fig. 3–6). Finally, because respondents with backup power were asked how much they paid on backup power before the experimental question, anchoring may have led to the backup owners' higher WTP. This final explanation would not explain the difference found between respondents who only owned solar/storage versus those who owned generators, as both these groups were exposed to the purchase price question.

In addition to showing the raw respondent WTP, Table 3–2 also shows the results as a % monthly bill and a $/kWh metric. These results have a smaller sample size due to three additional filtering steps we performed on the sample. First, we must drop respondents who skipped the monthly billing question. Second, we drop respondents who report having solar installed. Given net energy metering subsidies provided in

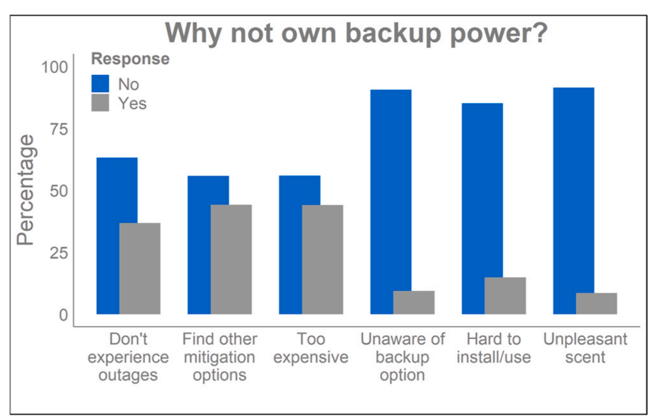

Fig. 3–4. Indication for why some respondents did not own backup power.

California, the presence of solar could undermine the meaning of the reported monthly billing data which is needed to convert the raw WTP figure. Third, we drop customers who report monthly bills less than $10, given the likelihood of erroneous data entry.

Despite the sample change, the results remain qualitatively the same. We find reductions in WTP to avoid outages as a result of the treatment notification but these reductions are not statistically significant. We

Table 3–1
Summary of WTP across key samples. Mean, Median, and various percentiles are presented to showcase the distribution of the results. Results are shared for the full sample as well as seven other subsamples (i.e. treatment assignment and backup ownership). The WTP survey question is found in the third section of the supplemental information.

WTP ($/month) for…	N	Mean	25th perc.	Median	75th perc.	95th perc.
Full Sample	2065	78.44	0	10	50	300
Households without notification	693	85.74	0	10	50	400
Households with 1-day notification	681	69.91	0	10	40	250
Households with 7-day notification	691	79.52	0	10	50	304.5
Households without backup power	1397	49.79	0	10	34	200
Households own generators	304	121.52	0	10	92.5	595.05
Households own solar+storage	243	97.56	0.5	20	100	381.9
Households own both gen. and sol+stor	121	262.60	0	20	100	1200

Table 3–2
Comparison of regression results across a variety of specifications.

	WTP ($/month) [1]	WTP ($/month) [2]	WTP ($/month) [3]	WTP ($/month) [4]	WTP (% bill) [5]	VoLL ($/kWh) [6]
Intercept	85.7431***	56.4235***	49.2175***	NA	46.5351***	10.2777***
	(11.086)	(11.9559)	(9.1346)		(6.6884)	(1.4772)
1-day notice	–15.8327	–14.3929	–13.4846	–24.8469	–6.2582	–1.382
	(15.7469)	(15.6068)	(13.8648)	(21.4403)	(9.1073)	(2.011)
7-day notice	–6.2222	–5.7045	–0.7902	–21.5694	–7.8372	–1.7309
	(15.6893)	(15.5483)	(14.7865)	(22.4991)	(8.5458)	(1.8874)
Back-up ownership	NA	83.2726***	74.7145***	79.5726***	17.6575*	3.900*
	NA	(13.3961)	(16.2609)	(20.256)	(10.5273)	(2.325)
Backup ownership control	No	Yes	Yes	Yes	Yes	Yes
Weighted	No	No	Yes	Yes	Yes	Yes
Robust s.e	No	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	No	Yes	No	No
Subsample	full	full	full	full	>$10, no solar	>$10, no solar
Total observations (n)	2065	2065	2065	2065	1629	1629
Ownership (n)	711	711	711	711	331	331

Note: *p<0.1; **p<0.05; ***p<0.01

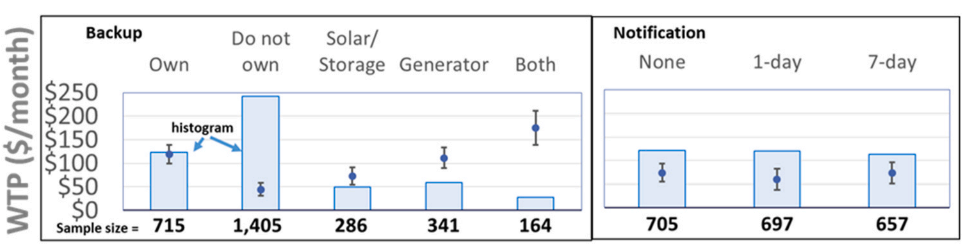

Fig. 3–5. Comparison of treatment effect with effect from backup ownership with 95% confidence intervals.

similarly find increases in WTP for the sample who own back-up power generators, though with less significance than the baseline results, likely because we drop roughly half of the backup power ownership sample since they own solar generators.

We calculate an average VoLL of $10–14/kWh, depending on whether respondents do not or do own backup power, respectively, which is within the range (i.e. $1/kWh - $25/kWh) of results found in prior stated preference literature reviews that measure WTP to avoid power outages (Schröder and Kuckshinrichs, 2015).

3.3. Heterogeneity analysis

Fig. 3–7 shows the distribution of responses to the experimental question, broken out by the randomized notification assignment. The significant overlap in the distributions of responses by notification in this figure corresponds to the regression analysis which found an statistically insignificant effect of notification on WTP.

We performed a descriptive analysis across the key demographic controls by running linear regressions of the WTP responses with each demographic control of interest and then comparing how the means and variances of WTP metrics vary by the different categories of the specific control specification. In effect, the below results are sample means by demographic factor, without controlling for backup power ownership.[9] Fig. 3–8 presents information on how the key financial controls (i.e. home type, home value, household income, and ownership status) correlate with the WTP to avoid power outages. We find little trend between home type and WTP.[10] We find that both home value and, to a lesser degree, income, are negatively correlated with respondents' WTP

[9] However, including relative WTP metrics once controlling for backup power led to similar results directionally.

[10] Of particular note is that when we run the regression when controlling for all demographic controls at once, the last categories of home type (i.e. mobile homes and RV / van ownership) become statistically different and lower than all other home category types. This result aligns with the intuition that individuals with these home types are likely less reliant on electricity from the grid.

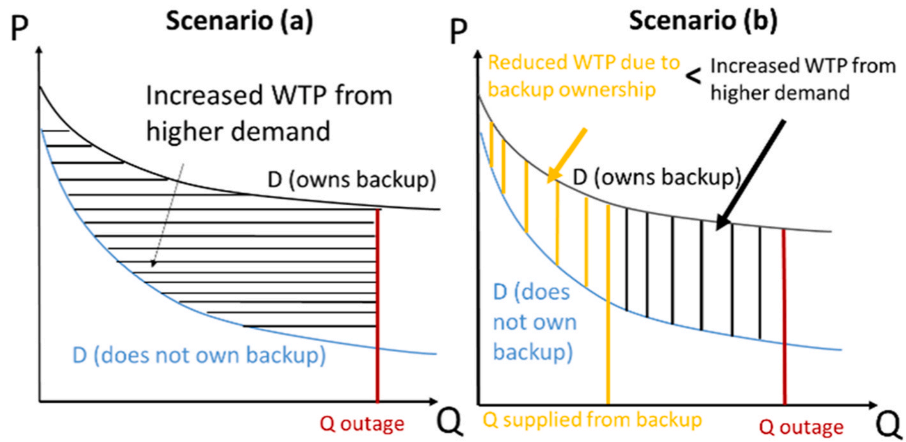

Fig. 3–6. Hypotheses of demand variation with backup power and relation to overall WTP.

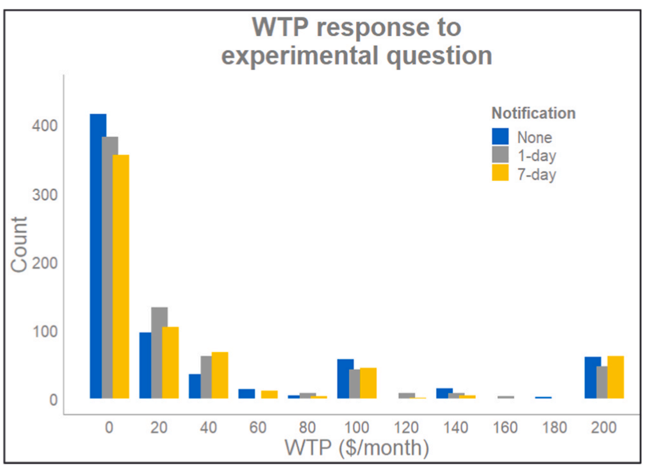

Fig. 3–7. Histogram on WTP by randomized notification.

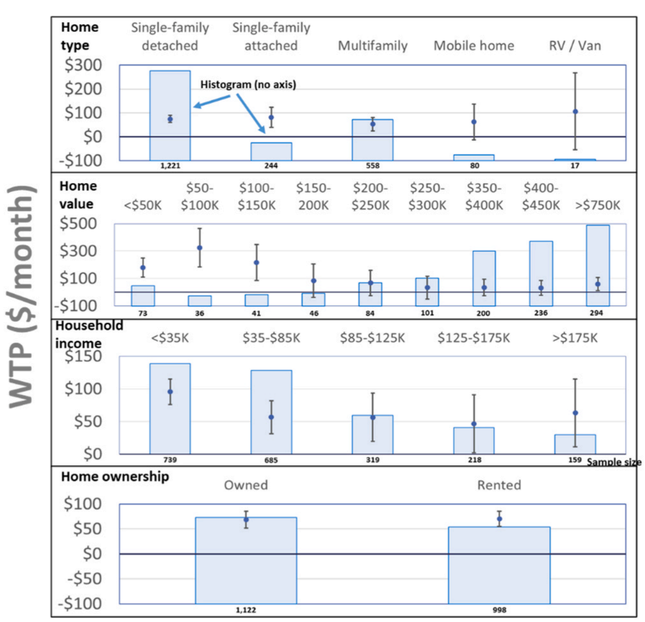

Fig. 3–8. Variation on WTP by respondent characteristics (home type, home value, home income, rental status).

to avoid outages, but both these correlations were weak. Nevertheless, this result suggests that, although high-income households likely have more ability to pay (as a function of their higher incomes), these respondents are less negatively impacted by outages than others. This may be due to these respondents having more substitution options available to mitigate the cost of a power outage. We do not find a correlation between income and backup power ownership in our sample, however. Prior work studying these trends, though limited, has found positive correlations between income and WTP to avoid power outages, but like our results, those trends were not strong (Baik et al., 2020). More results discussing other demographic controls are presented in the supplemental information.

4. Conclusion

In the open-ended stated-preference experiment, we found positive and statistically significant WTP to avoid power outages, consistent with the expectation that outages are costly to the residential sector. Furthermore, we found that advanced notice of a power outage can reduce the WTP to avoid those power outages by 10–20%, consistent with the expectation that notice can allow customers to plan substitution strategies that help mitigate power outage costs. However, these notification effects are not statistically significant. The insignificance of the effect suggests that other factors we study (e.g. backup ownership) or that other researchers study (e.g. customer type and outage duration) may have a more important impact on WTP, and by extension, on the negative impacts of outages on households, compared to outage notification. Without a statistically significant result on advance warning, our results provide no direct support for evaluating programs based on notification timing, such as a comparison between PSPS and EPSS programs. These results were robust over several regression specifications that controlled for demographic variables and applied the survey weights provided by NORC. While PSPS programs have the potential to provide advanced notice of a power outage, EPSS programs are not able to do so. In the two years since the data for this study were collected, there has been an increase in usage of EPSS programs in relation to PSPS programs (Hagler et al., 2023).

Though the notification results are not statistically significant, our results do indicate that the value of advance notice increases with timing, and that the question of the value of advance notice should continue to be studied. This is particularly important in light of this study's results with respect to heterogeneity in WTP and in light of the increased usage of EPSS. For example, we found that household wealth (proxied using estimated home value) is negatively correlated with WTP. We found limited variation in WTP by home type and home ownership status, but confirming statistical significance of these results would require larger sample sizes than we studied. Considering these trends, our study's weak result with respect to advanced notice suggests that further research on this topic is important.

On average, respondents did not have high expectations for the number of future outage hours. This result was true even when segmenting out customers who experienced a sustained power outage between 2019 and 2021. Such a result implies that households in California might expect limited impact from future PSPS and EPSS events. Such expectations could be, in part, driven by the significant investments in enhanced resilience to wildfires California utilities have been and plan to make. As of 2023, the California's two largest utilities were proposing expenditures greater than $23 billion in areas of system hardening and vegetation management (Balaraman, 2023). Future researchers could study how electricity consumer expectations may or may not lead to defensive investments that might mitigate power outage costs as well as investigate appropriate levels of resiliency investment for electric utilities.

Finally, as indicated in the introduction, while our study focused on backup ownership and outage notification, other outage contexts like outside weather conditions (i.e. extreme hot or cold during outage) or geographic exposure (i.e. widespread or contained outage) could influence WTP estimation. Future work could expand on our results to study how different power outage contexts might impact WTP and interact with our advanced outage notification.

CRediT authorship contribution statement

Duncan Callaway: Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Will Gorman:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Do notifications affect consumers willingness to incur power outages? Evidence from Public Safety Power Shutoffs in California (Original data) (OSF) https://osf.io/tcg8p/.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.tej.2024.107385.

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