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Health and financial impacts of demand-side response measures differ across sociodemographic groups

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Demand-side response (DSR) measures, which facilitate the integration of high shares of intermittent renewable generation into electric grids, are gaining prominence. DSR measures, such as time-of-use (TOU) rates, charge higher rates during high-demand 'on-peak' times. These rates may disproportionately impact the energy bills and health of vulnerable households, defined as those who face greater energy needs combined with greater social and financial pressures. Here we examine 7,487 households that took part in a randomized control TOU pilot in the southwestern United States. We found that assignment to TOU rather than control disproportionately increases bills for households with elderly and disabled occupants, and predicts worse health outcomes for households with disabled and ethnic minority occupants than those for non-vulnerable counterparts. These results suggest that vulnerable groups should be considered separately in DSR rate design, and future pilots should seek to determine which designs most effectively avoid exacerbating existing energy injustices or creating new ones.

To mitigate climate change, electricity grids need to integrate large shares of renewable generation. Some renewables, such as solar, are variable and cannot be generated according to market needs, which creates challenges in matching supply with demand. Demand-side response (DSR) measures are gaining prominence as a way to align demand with non-dispatchable supply. The residential sector accounts for 30–40% of electricity consumption across the Organisation for Economic Co-operation and Development countries, which makes it a prime target for DSR[1]. Decision makers, such as the California Public Utilities Commission, are enacting policies that require default enrolment in DSR programmes[2], which can yield participation rates that exceed 80% (ref. [3]); other entities may follow[4]. Thus, DSR is poised to soon reach millions of households, which highlights the need to understand whether the costs and benefits of DSR are distributed evenly across sociodemographic groups.

DSR measures typically use price signals to attempt to shift demand away from high-demand 'on-peak' times. Static time-of-use (TOU) rates are a common DSR measure that aim to shift electricity use away from on-peak times using a fixed rate schedule with more expensive on-peak times. For households that already struggle with electricity bills, this can be detrimental[5–8]. Households suffering from energy poverty are forced to make trade-offs between paying for electricity bills versus other necessities, such as food and medicine[5,6,9,10]. TOU and other forms of DSR may worsen this trade-off pressure, often termed 'the heat or eat dilemma'.

The term 'energy poverty' broadly refers to a confluence of factors that result in the inability to maintain a dwelling at a comfortable and healthy temperature, failure of which is associated with increased mortality and morbidity, and having to make decisions between paying for electricity or other necessities such as food[7,9–11]. Energy poverty is often considered synonymous with 'fuel poverty'[12], and assesses the same sets of concerns addressed by some definitions of energy insecurity[13].

Energy poverty can be considered a state of being in which households face an inability to meet both energy and other costs necessary to live a decent life[8]. In contrast, energy vulnerability is dynamic, with energy-vulnerable households characterized as those that "face a combination of more intense and non-negotiable energy needs as well as a lack of social and/or financial capital".[8] Energy-vulnerable households have a limited capacity to adapt to changing circumstances, such as TOU assignment[8].

Further, energy-vulnerable groups face energy injustices: procedural injustice in limited access to information, policy participation and legal rights; distributional injustice in inequalities in income, energy prices and housing efficiency; and injustice in recognition, which is a lack of recognition of the differential needs of energy-vulnerable groups, and an unequal accordance of respect[14]. Walker and Day[14] provide in-depth discussions of these topics. Below, we draw on energy poverty and energy justice literature to define vulnerability indicators.

Low-income households face pressure to curtail energy costs, often with negative impacts[8]. For instance, during winter months with high heating bills, low-income households curtail energy use to thermally uncomfortable levels[6]. Electricity shut-offs that result from utility debt can exacerbate both physical and mental health conditions[5], and low incomes are linked to a higher likelihood of mortality during extreme heat events[15–18]. Lower incomes are linked to distributional injustices, which include higher likelihood of living in inefficient buildings with poor insulation and less efficient appliances, which means these homes are more expensive to heat (or cool) than others[5,14,19–21].

Elderly people are at risk of recognition injustices. They require a narrower band of temperatures for health[22] and suffer exacerbated mortality during both extreme heat and extreme cold if unable to maintain the appropriate temperatures[23–26]. As a case in point, heat waves in Italy and France in 2003 were associated with higher mortality rates for elderly individuals[17,18]. Elderly people also experience

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Table 1 | Definition of vulnerability on each indicator used in the quantitative analyses

Low income	Enrolled in electric utility financial aid programme; some eligible households probably did not complete the enrolment process, so this indicator may be imperfect
Elderly	Someone over the age of 65 resides in the household
Young children	Someone under the age of 6 resides in the household
Disability	Someone in the household has a disability or serious medical condition that requires the 'home to be cool in the summer', or that requires them to 'use more energy for medical equipment'; although this does not cover the full range of reasons for which a person with a disability may need to use additional energy, available data preclude such a nuanced examination
Hispanic	Respondent identified as Hispanic. Respondents that identified as non-Hispanic white are considered non-vulnerable. Other households (for example, those that identified as Asian American) could not be considered non-vulnerable in terms of ethnicity/race. Thus, all analyses using the Hispanic vulnerability indicator use a subsample that comprises only Hispanic and non-Hispanic white participants, and the Hispanic indicator is not included as a control in other analyses
African American	Respondent identified as African American. All analyses using the African American vulnerability indicator use a subsample that comprises only African American and non-Hispanic white respondents, and the African American indicator is not included as a control in other analyses

Supplementary Table 1 gives descriptive statistics. The survey question text is provided in Methods.

greater difficulty paying for food during seasons with high heating or cooling needs, compared to the general population[27].

Families with young children experience heightened pressures and thus are at risk of recognition injustices. Households with children bear additional costs associated with ensuring that children are well fed and healthy[5], and thereby face greater competing (childcare) expenses and hence more challenges to meet their energy needs. Children living in energy poverty are more likely to face food scarcity and to have health and developmental issues, compared to those not in energy poverty[28]. Young children are also at higher risk of morbidity in extreme heat events[25,26].

People with disabilities face higher rates of energy poverty[10]. Compared to the general population, people with disabilities may need more energy to realize a range of essential capabilities[24]. Illness or disability can limit freedom of movement, which raises energy costs due to people being at home more[8]. Although previous work has not found disability to predict mortality during heat events[29], financial pressure to curtail electricity use may contribute to poorer health outcomes. The energy needs of those with disabilities vary greatly depending on the individual and disability, but are likely to involve a higher energy use. Yet, the needs of individuals with disabilities are often systematically disregarded by decision makers (recognition and procedural injustices[14]).

Finally, racial and ethnic minorities face procedural injustices in the form of discrimination in areas such as housing, employment and credit[30], in addition to a lack of informed consent for energy projects, lack of representation in the decision-making and lack of access to information[14,31]. Distributional injustices arise from these procedural injustices, and racial minorities are more likely to live in inefficient housing that necessitates higher energy bills to control indoor temperatures compared to the non-minority counterparts[32,33]. Racial and ethnic minorities may also face greater health impacts tied to inability to cool homes; the likelihood of death during an extreme heat event in the United States is linked to sociodemographic vulnerability, defined partly by ethnic minority and Latino immigrant status[15,34].

Some argue that low-income households can save money on static TOU rates because their existing patterns place most of their use away from on-peak times[35]. However, work that examined critical peak pricing found that, at baseline, low-income and elderly households tend to have a lower-than-average use during on-peak times, whereas households with chronically ill members tend to have a higher on-peak use[36]. Beyond existing use patterns, demand flexibility is considered key for households to be able to take financial advantage of TOU[37]. Vulnerable households may face constraints that limit the flexibility of electricity use timing, such as poorly insulated homes that prevent the retention of comfortable temperatures if heating or cooling systems are turned off[5,32,33,38]. Some DSR trials found that vulnerable (low-income, young children, elderly and/or chronically ill) households can load shift on par with or to a greater extent than non-vulnerable households[36,39–41]. However, other work found that vulnerable (low-income and young children) households load shift less and/or have a higher demand during on-peak times and limited flexibility compared to non-vulnerable households[39,42–44]. Overall, it is unclear how TOU rates will impact vulnerable households in terms of bill changes, and responses will probably differ by group. There is a risk that those with higher and less flexible energy needs, such as the elderly or those with a disability, will face bill increases.

Energy poverty has been associated with a range of negative health outcomes, particularly regarding respiratory health[45]. Although much work examines the links between energy poverty and discomfort, illness and mortality in cold climates[11,46–48], less work has examined these links related to extreme heat. Prior work identified that greater thermal discomfort associated with energy poverty is tied to an increased likelihood of negative impacts on both physical and mental health among households in cold climates[45,49]. The vulnerable groups that we focus on have been found to suffer worse outcomes during extreme heat events[15–18,25,26,34]; this may be linked to the inability to access sufficient cooling, but has not yet been examined in the context of energy poverty.

Here we evaluate the cost and health impacts of TOU among vulnerable (that is, low income, elderly, disability, young children and racial/ethnic minority; Table 1 gives the operational definitions) versus non-vulnerable households that took part in a randomized control TOU pilot in the southwestern United States. We found that, although all households on TOU face bill increases relative to controls, those vulnerable on the elderly and disability indicators face greater bill increases on TOU versus control than their non-vulnerable counterparts. Conversely, low-income and Hispanic households face relatively smaller bill increases on TOU versus control than their non-vulnerable counterparts. Households vulnerable on low-income and disability indicators face worse health outcomes regardless of the rate. Relative to their non-vulnerable counterparts, households vulnerable on disability and Hispanic indicators face an increased likelihood of negative health outcomes when assigned to TOU, and low-income households face increased discomfort. These results suggest the need to consider vulnerable groups separately, and the importance of a careful rate design.

Effect of TOU on electricity bills

All analyses were performed using STATA MP 14.2. The pilot included two TOU rates and a non-TOU control group. Compared

Table 2 | Triple difference estimators examining mean monthly bills (US$) for TOU1, by vulnerability group

	(1)	(2)	(3)	(4)	(5)	(6)
	Low income	Elderly	Young children	Disability	Hispanic	African American
TOU1×Vulnerable×Pilot	1.11 (2.53)	3.69 (2.72)	0.72 (3.89)	8.65* (3.38)	−3.79 (3.29)	−4.43 (5.94)
TOU1×Pilot	13.35*** (1.88)	12.59*** (1.71)	13.84*** (1.43)	12.42*** (1.48)	15.83*** (1.86)	15.83*** (1.86)
Vulnerable×Pilot	−5.18** (1.59)	0.36 (1.69)	1.15 (2.52)	1.25 (2.03)	2.69 (2.03)	1.76 (3.98)
Vulnerable×TOU1	−5.72 (5.28)	−2.40 (6.02)	3.33 (7.98)	3.94 (7.57)	0.02 (7.15)	2.02 (11.76)
TOU1	−3.81 (4.06)	−3.34 (3.73)	−4.53 (3.19)	−4.71 (3.23)	−2.76 (4.24)	−2.76 (4.24)
Pilot	6.18*** (1.18)	3.94*** (1.06)	3.92*** (0.88)	3.85*** (0.93)	3.32** (1.14)	3.32** (1.14)
Vulnerable	−52.72*** (3.40)	−3.69 (3.78)	5.14 (4.95)	5.11 (4.73)	−23.33*** (4.42)	−34.36*** (7.39)
R^2	0.08	0.00	0.00	0.01	0.01	0.01
n	9,738	9,738	9,738	9,738	7,364	5,862

Standard errors in parentheses. $^*P<0.05$; $^{**}P<0.01$; $^{***}P<0.001$.

Table 3 | Triple difference estimators examining mean monthly bills (US$) for TOU2, by vulnerability group

	(1)	(2)	(3)	(4)	(5)	(6)
	Low income	Elderly	Young children	Disability	Hispanic	African American
TOU2×Vulnerable×Pilot	−6.21* (2.46)	8.76*** (2.63)	5.31 (4.18)	7.49* (3.27)	−7.70* (3.12)	−6.27 (5.81)
TOU2×Pilot	26.45*** (1.92)	19.96*** (1.65)	22.98*** (1.36)	22.18*** (1.43)	27.92*** (1.84)	27.92*** (1.84)
Vulnerable×Pilot	−5.18** (1.59)	0.36 (1.69)	1.15 (2.52)	1.25 (2.03)	2.69 (2.03)	1.76 (3.98)
Vulnerable×TOU2	3.36 (4.83)	3.06 (5.34)	2.58 (7.17)	4.48 (6.63)	−3.51 (6.21)	6.99 (10.15)
TOU2	−8.03* (3.81)	−9.26** (3.44)	−8.22** (2.86)	−8.88** (2.93)	−6.51 (3.83)	−6.51 (3.83)
Pilot	6.18*** (1.18)	3.94*** (1.06)	3.92*** (0.88)	3.85*** (0.93)	3.32** (1.14)	3.32** (1.14)
Vulnerable	−52.72*** (3.40)	−3.69 (3.78)	5.14 (4.95)	5.11 (4.73)	−23.33*** (4.42)	−34.36*** (7.39)
R^2	0.08	0.01	0.01	0.01	0.02	0.02
n	10,966	10,966	10,966	10,966	8,414	6,700

Standard errors in parentheses. $^*P<0.05$; $^{**}P<0.01$; $^{***}P<0.001$.

to TOU Rate 1 (TOU1), TOU Rate 2 (TOU2) had higher cents per kilowatt hour costs on-peak and fewer hours on-peak (Methods).

The pilot happened during summer in a hot climate in the southwestern United States; bills were expected to be driven by cooling needs. We used a difference-in-difference-in-differences (triple difference) approach to examine whether assignment to TOU results in greater electricity bill increases for vulnerable versus non-vulnerable households. Supplementary Table 2 presents the mean monthly bill amounts for all the study groups across the baseline and pilot periods. Each model compares the control to either TOU1 (Table 2) or TOU2 (Table 3). There are six models for each rate, one for each vulnerability indicator. The mean monthly summer bill amount is the dependent variable, and independent variables are the full set of interaction terms and main effects required for a triple difference model (Methods).

Both TOU rates resulted in bill increases for all participants ($P=0.000$; Fig. 1, Tables 2 and 3 and Supplementary Note 1). The triple difference term TOU×Vulnerable×Pilot in each model gives the estimated effect of the TOU assignment for vulnerable individuals during the pilot year (Methods). As expected, households vulnerable on the disability indicator assigned to TOU1 ($P=0.011$) or TOU2 ($P=0.022$) and households vulnerable on the elderly indicator assigned to TOU2 ($P=0.001$) saw greater baseline-to-pilot-year bill increases compared to non-vulnerable counterparts. Contrary to expectations, for households vulnerable on the low-income ($P=0.012$) and Hispanic indicators ($P=0.014$), assignment to TOU2 versus control is associated with a smaller increase in bills relative to non-vulnerable households. Other groups (African American and young children) saw no difference in TOU assignment impacts versus their non-vulnerable counterparts. The remaining model terms primarily serve as controls, and are discussed in Supplementary Note 1.

On-peak energy use reduction

In Tables 2 and 3, R^2 is consistently <0.10, which suggests that factors not included in the model contribute to bill variation. Regional fixed effects analysis confirms that changes in on-peak use predict bill changes (Supplementary Note 2 and Supplementary Tables 1–3). In a separate triple difference analysis (parallel to the billing analysis (Methods)), we found that households vulnerable on the disability indicator saw a smaller decrease in on-peak use from baseline to pilot year when on TOU1 versus control, compared to their non-vulnerable counterparts; no differences were observed for other groups (Supplementary Tables 7 and 8; the mean on-peak use reported by group and time period is given in Supplementary Table 6). Additionally, examining reported behavioural efforts to curtail on-peak air conditioning (AC) use (Table 4), low-income, young children, Hispanic and African American households reported a greater curtailment compared to their non-vulnerable counterparts, whereas households with elderly members reported less curtailment; no differences were observed for households with versus without a disability (Wilcoxon rank sum tests (Methods)).

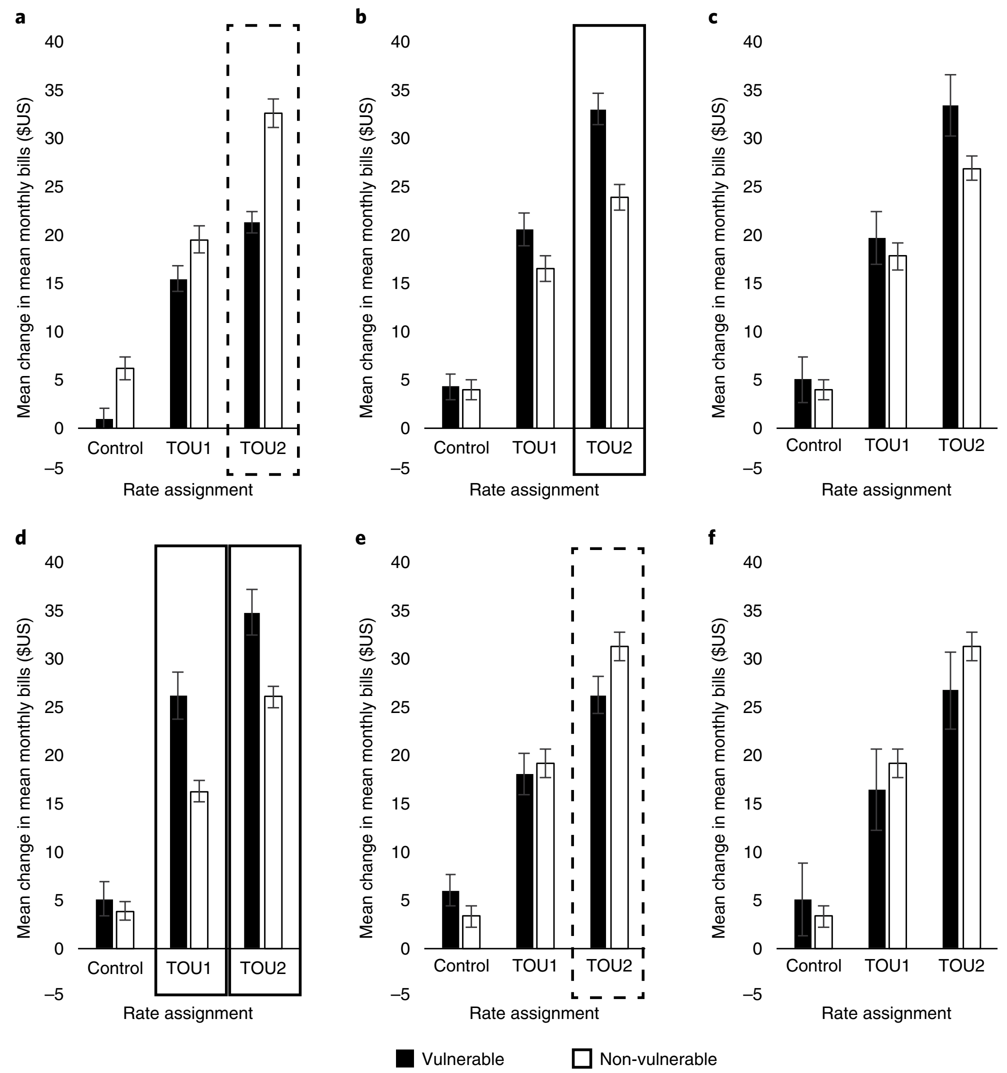

Fig. 1 | Mean change in mean monthly summer bills, by vulnerability group and rate assignment. Change in mean monthly summer bills (pilot minus baseline) for the control, TOU1 and TOU2 rate groups for each vulnerability indicator with standard error bars. **a**, Low income (control, $n=2,865$; TOU1, $n=2,004$; TOU2, $n=2,618$). **b**, Elderly (control, $n=2,865$; TOU1, $n=2,004$; TOU2, $n=2,618$). **c**, Young children (control, $n=2,865$; TOU1, $n=2,004$; TOU2, $n=2,618$). **d**, Disability (control, $n=2,865$; TOU1, $n=2,004$, TOU2, $n=2,618$). **e**, Hispanic (control, $n=2,202$; TOU1, $n=1,480$; TOU2, $n=2,005$). **f**, African American (control, $n=1,762$; TOU1, $n=1,169$; TOU2, $n=1,588$). Solid boxes denote a positive triple difference term that indicates a greater increase in bills for vulnerable versus non-vulnerable groups; dashed boxes denote a negative triple difference term that indicates a smaller increase in bills for vulnerable versus non-vulnerable groups (Tables 2 and 3).

Table 4 | Reported AC curtailment by vulnerable households versus non-vulnerable counterparts

	Vulnerability present (mean curtailment)	Vulnerability absent (mean curtailment)	*z* score	*P*	*d*[a]
Low income	**3.30**	3.10	−4.85	0.000	0.16
Elderly	3.09	**3.24**	3.73	0.000	0.12
Young children	**3.33**	3.16	−2.80	0.005	0.13
Disability	3.12	3.20	1.72	0.086	0.06
Hispanic	**3.29**	3.02	−5.54	0.000	0.22
African American	**3.45**	3.02	−5.27	0.000	0.35

Main sample, $n=4,129$; Hispanic subsample, $n=3,108$; African American subsample, $n=2,459$). Bold font shows the group that made greater efforts to curtail for each behaviour. [a]Cohen's *d* effect size.

Health impacts of TOU assignment

We tested whether vulnerable versus non-vulnerable households report a higher likelihood of seeking medical attention for heat-related reasons, using regional fixed effects regression grouped by climate zone (Methods and Supplementary Tables 9 and 10). The dependent variable is the likelihood of seeking medical attention. Independent variables in all models are rate assignment and vulnerability indicators for low income, elderly, young children and disability. Hispanic and African American indicators appear only in models that use subsamples. Interaction terms Vulnerable×TOU are introduced individually in subsequent models to test group-specific effects of TOU assignment. The frequency of reported discomfort (expected precursor to more severe problems), presence of AC (expected to impact indoor temperature), change in on-peak use (expected to impact indoor temperature) and home ownership (expected to impact indoor temperature via a greater control by homeowners over efficiency measures, such as insulation) are included as control variables in all models. A subset of the models is presented in Table 5, which comprises all the main effects models and models with significant vulnerability interaction terms at $P < 0.05$.

Main effects indicate that households vulnerable on low-income ($P = 0.000$), disability ($P = 0.000$) and Hispanic indicators ($0.001 < P < 0.011$) are more likely to seek medical attention for heat-related reasons (Table 5). TOU assignment alone does not predict the likelihood of seeking medical attention. A greater frequency of discomfort predicts a higher likelihood of needing medical attention for heat-related reasons in all models ($P = 0.000$), whereas home ownership predicts a lower likelihood of needing medical attention in models (1), (2), (3) and (4) ($0.011 < P < 0.032$) and a reduction in on-peak use predicts a higher likelihood of needing medical attention in models (7), (8) and (9) ($0.011 < P < 0.014$) (Table 5).

Considering the interaction terms, TOU versus control assignment significantly alters the likelihood of seeking medical attention among households with either young children ($P = 0.045$) or disabled members assigned to TOU1 ($P = 0.030$), and Hispanic households assigned to TOU2 ($P = 0.032$). For significant interaction terms, we performed post hoc tests with the conservative Scheffé's adjustment applied to significance testing of the contrast between pairwise comparisons (Table 6). Among families with young children, assignment to TOU1 versus control correlates with a lower likelihood of needing medical attention. For households vulnerable on the disability indicator, assignment to TOU1 is associated with a higher likelihood of seeking medical attention relative to non-vulnerable households on TOU1 (and non-vulnerable households assigned to control rate). Hispanic households assigned to TOU2 face higher a likelihood of needing medical attention than non-Hispanic white households on TOU2.

Discomfort in vulnerable versus non-vulnerable households

We tested whether vulnerable versus non-vulnerable households report more frequently experiencing discomfort due to homes being too hot, using regional fixed effects regression grouped by climate zone (Methods and Supplementary Tables 11 and 12). The dependent variable is the frequency of discomfort experienced while trying to save money on electricity. Independent variables are rate assignment, vulnerability indicators and Vulnerability×TOU interaction terms. The models examine the interaction terms for each vulnerable group separately. The presence of AC, change in on-peak use and home ownership are included as control variables in all the models.

Regardless of the rate assignment, low-income ($P = 0.000$), disability ($P = 0.000$) and Hispanic indicators ($P = 0.024$, Hispanic for TOU1 models only) predict more frequent discomfort, whereas the elderly indicator ($P < 0.042$) predicts less frequent discomfort. Two interaction terms are significant: Low income×TOU1 and African American×TOU1. For these terms, we performed post hoc tests with Scheffé's adjustment (Table 7). Low-income households assigned to TOU face a higher discomfort than their non-vulnerable counterparts assigned to TOU (this is also true for the control group). No significant differences were observed for the African American×TOU interaction term.

Discussion

The results suggest distributional, procedural and recognition injustices that differ across groups, which highlights the importance of considering specific subpopulations in the design and rollout of DSR programmes. The greater cost increases experienced by households vulnerable on the disability and elderly indicators assigned to TOU, relative to their non-vulnerable counterparts, suggest recognition injustices[14]. Cost increases faced by these households probably stem from inability to shift use times, as evidenced in our findings that households vulnerable on the disability indicator reduced on-peak use less than their non-vulnerable counterparts, and households vulnerable on both disability and elderly indicators reported less AC curtailment compared to their non-vulnerable counterparts. These groups may be constrained in load shifting due to being home-bound and having a greater reliance on energy for medical equipment, temperature control and completing daily tasks[8,23–26].

Households vulnerable on low-income and disability indicators face worse health and comfort outcomes than the outcomes faced by non-vulnerable counterparts, regardless of rate assignment, which probably stems from ongoing procedural and distributional injustices. However, TOU appears to widen the difference in health outcomes between those vulnerable on the disability indicator and their non-vulnerable counterparts, which suggests recognition injustices given that this group already struggles to keep homes cool under current distributional injustices.

TOU similarly correlates with worse health outcomes for Hispanic households, relative to their non-vulnerable counterparts. Hispanic households reported greater curtailment of AC compared to non-Hispanic white households, and it is possible that this contributed to negative health outcomes. Hispanic groups are more likely to experience heat distress in extreme heat events[15,34], which raises concerns that further distributional injustice could worsen the differentials in mortality rates. Future research should evaluate whether this outcome is linked to inefficient homes that limit the ability to keep cool[33].

Our finding that TOU1 only shows a differential cost effect for those with disabilities, whereas TOU2 shows differential cost effects for those vulnerable on the low-income, elderly, disability and Hispanic indicators, suggests that the design of TOU rates is important in predicting outcomes for energy-vulnerable populations. Specifically, the length and kilowatt hour expense of on-peak times appear to play an important role in the group-differentiated financial impacts of TOU.

Given that DSR rates will probably be needed to integrate higher shares of non-dispatchable generation, it is important for pilots to continue trialling multiple rate designs and evaluating the impacts on vulnerable populations, with the goal of identifying rate designs in each locale that meet energy integration needs without worsening or creating energy injustices. The TOU rates examined here increased electricity bills for all groups. By definition, vulnerable groups are less able to bear cost increases than their non-vulnerable counterparts[8], which suggests that switching to the TOU rates considered in this study probably increased hardships such as the 'heat or eat' dilemma. However, compared to their non-vulnerable counterparts, only two groups (disability and elderly) experienced greater cost increases, whereas two groups (low income and Hispanic) experienced lower cost increases.

TOU rate design should aim to be cost neutral, and studies of other TOU rates have found evidence that some rate designs can, indeed, achieve cost neutrality across the general population[50]. If the TOU rate in our study had achieved cost neutrality across the general population, rather than causing increases across the board, it is possible that only some of the vulnerable groups examined (elderly and disability) would have been worse off, whereas some (low income and Hispanic) may have been better off. More extensive examination of potential rate designs is needed to understand if

Table 5 | Regional fixed effects logit model grouped by climate zone, predicting likelihood of a household member needing medical attention

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Main effects, TOU1	**Young children in interaction, TOU1**	**Disability in interaction, TOU1**	**Main effects (Hispanic), TOU1**	**Main effects (African American), TOU1**	**Main effects, TOU2**	**Main effects (Hispanic), TOU2**	**Hispanic in interaction, TOU2**	**Main effects (African American), TOU2**
Vulnerable×TOU		−0.71* (0.35)	0.60* (0.28)					0.38* (0.18)	
Assigned to TOU	−0.07 (0.14)	0.06 (0.19)	−0.38** (0.12)	0.02 (0.21)	0.05 (0.26)	−0.06 (0.10)	−0.02 (0.15)	−0.20 (0.15)	−0.29* (0.14)
Low income	0.57*** (0.14)	0.57*** (0.14)	0.59*** (0.14)	0.58*** (0.16)	0.69*** (0.17)	0.70*** (0.14)	0.82*** (0.18)	0.81*** (0.18)	0.99*** (0.26)
Elderly	0.26 (0.16)	0.27 (0.16)	0.26 (0.16)	0.22 (0.19)	0.24 (0.23)	0.09 (0.09)	0.17 (0.09)	0.17 (0.09)	0.35 (0.22)
Young children	0.33 (0.19)	0.59** (0.21)	0.33 (0.18)	0.18 (0.24)	−0.12* (0.05)	0.47 (0.25)	0.36 (0.35)	0.37 (0.35)	0.11 (0.38)
Disability	1.58*** (0.16)	1.59*** (0.16)	1.36*** (0.15)	1.72*** (0.19)	1.69*** (0.18)	1.40*** (0.12)	1.42*** (0.19)	1.41*** (0.19)	1.17*** (0.16)
Hispanic				0.36 (0.14)			0.49** (0.15)	0.32 (0.21)	
African American					0.42 (0.23)				0.30 (0.18)
Presence of AC	0.14 (0.21)	0.14 (0.21)	0.13 (0.22)	0.43* (0.22)	0.62 (0.76)	0.18 (0.39)	0.01 (0.55)	0.01 (0.56)	0.40 (0.60)
Frequency of discomfort trying to save money	0.80*** (0.05)	0.80*** (0.05)	0.80*** (0.05)	0.76*** (0.06)	0.82*** (0.05)	0.85*** (0.06)	0.92*** (0.05)	0.92*** (0.06)	0.88*** (0.10)
Change in on-peak use (kWh, daily average)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.05 (0.03)	0.08 (0.05)	0.07+ (0.04)	0.11* (0.04)	0.11* (0.04)	0.15* (0.06)
Home owned	−0.35* (0.15)	−0.35* (0.15)	−0.33* (0.16)	−0.38* (0.15)	−0.36 (0.30)	−0.31 (0.22)	−0.25 (0.29)	−0.25 (0.28)	−0.30 (0.45)
Pseudo R^2	0.20	0.20	0.20	0.21	0.22	0.19	0.22	0.22	0.20
n	4,869	4,869	4,869	3,682	2,931	5,483	4,207	4,207	3297

Standard errors in parentheses, clustered by climate zone. $^{*}P<0.05$; $^{**}P<0.01$; $^{***}P<0.001$.

Table 6 | Post hoc tests of Vulnerable×TOU interaction terms on the need for medical attention

	Control, vulnerable versus	TOU, non-vulnerable versus	TOU, vulnerable versus
Young children×TOU1			
Control, non-vulnerable	0.59* (0.21)	0.06 (0.19)	−0.6 (0.25)
Control, vulnerable		−0.53* (0.16)	−0.65* (0.21)
TOU, non-vulnerable			−0.12 (0.30)
Disability×TOU			
Control, non-vulnerable	1.38* (0.16)	−0.08 (0.11)	1.34* (0.20)
Control, vulnerable		−1.45* (0.10)	−0.03 (0.19)
TOU, non-vulnerable			1.43* (0.17)
Hispanic×TOU2			
Control, non-vulnerable	0.32 (0.21)	−0.10 (0.15)	0.50* (0.15)
Control, vulnerable		−0.52 (0.27)	0.18 (0.21)
TOU, non-vulnerable			0.70* (0.14)

Pairwise comparison, contrast. Standard error in parentheses. *Scheffé test significant at the 95% level.

Table 7 | Post hoc tests of Vulnerable×TOU interaction terms on discomfort

	Control, vulnerable versus	TOU, non-vulnerable versus	TOU, vulnerable versus
Low income×TOU1			
Control, non-vulnerable	0.32* (0.48)	0.06 (0.02)	0.28* (0.05)
Control, vulnerable		−0.26* (0.04)	−0.03 (0.04)
TOU, non-vulnerable			0.23* (0.04)
African American×TOU			
Control, non-vulnerable	−0.17 (0.10)	−0.02 (0.03)	0.08 (0.12)
Control, vulnerable		0.15 (0.12)	0.26 (0.09)
TOU, non-vulnerable			0.11 (0.13)

Pairwise comparison, contrast. Standard error in parentheses. *Scheffé test significant at the 95% level.

this would be borne out in practice. Given that those vulnerable on disability and elderly indicators have a greater need for affordable energy compared to the general population, policy or rate design interventions should ensure that energy costs are low enough for these groups to maintain their health on TOU or other DSR rates and still be able to afford other necessities[24].

As opt-out DSR programmes spread, it is important that the costs of each DSR rate relative to those of other offered rates are clearly communicated and that the opt-out procedures be made clear to all, particularly vulnerable groups who are at risk of unfavourable outcomes on DSR. To aid households in evaluating benefits and burdens of competing rates, it is important to communicate cost information in a way that minimizes cognitive burden[51,52]. Using heuristics to address common misperceptions may improve household understanding of energy use[53]. Given prior findings that households often base decisions regarding TOU enrolment on perceived financial savings, but misperceive the extent of actual financial savings[54], further testing of an ideal choice architecture and information presentation for DSR is critical to facilitate all households making informed decisions about their electricity rates.

More broadly, our findings regarding the worse health and comfort outcomes for households vulnerable on low-income and disability indicators regardless of rate assignment suggest that energy-vulnerable groups in hot climates globally should be the focus of future research. These findings also suggest a need for policy intervention to support more affordable cooling, regardless of future DSR rollout. Cooling centres may help reduce discomfort, but often operate only during weekday business hours, so are disruptive to family routines and provide only part-time relief[55]. Thus, we recommend other measures, such as improving building and appliance energy efficiency, and carefully designed rates. Efficiency improvement programmes can offer large cost savings and reduce emissions, as well as decrease discomfort[56,57]. Future research should directly consider the extent to which housing energy efficiency limits the ability to control bills on DSR rates such as TOU, with a view to informing the design of complementary policies to address distributional injustices.

Our results should be viewed in the light of several limitations. First, our sample comprised individuals who opted into the pilot. Thus, our sample may be less risk averse than the general population[58,59], or may have a greater expectation of monetary savings on TOU[60]. Second, the results may not generalize to all populations. Survey completers had higher mean baseline use and larger mean bill increases than partial completers. Control group members were more likely to complete the survey than those assigned to TOU1. Several vulnerable groups (low income, elderly, disability, Hispanic and African American) were less likely to complete the survey compared to non-vulnerable counterparts. Possibly survey completers had fewer time pressures, which suggests conservative estimates of the impact on vulnerable groups. Third, our indicator for low-income households relied on enrolment in a utility programme, and thus probably underestimates the low-income households sampled and has an imperfect separation between vulnerable and non-vulnerable households; the associated coefficients should be interpreted with caution. Fourth, we examined vulnerability indicators in isolation, and hence the results do not capture differential impacts faced by those bearing a double burden, such as being both elderly and low income.

TOU raised the cost of energy for all households in our study, but some vulnerable households (elderly and disability) face greater bill increases on TOU compared to their non-vulnerable counterparts. Households vulnerable on low-income and disability indicators also face more discomfort and more heat-related medical issues regardless of rate assignment, which raises general concerns about the health impacts of energy poverty in hot climates. TOU widens the discomfort gap (low income) and increases the likelihood of seeking medical attention (disability and Hispanic) of some vulnerable groups relative to non-vulnerable counterparts on TOU. Rate design plays an important role in the impact of price-based DSR measures on vulnerable households, and future pilots should continue to examine multiple potential rate designs to determine which designs most effectively avoid exacerbating existing energy injustices or creating new ones.

Methods

Ethics statement. The University of Southern California's University Park Institutional Review Board reviewed and approved this research, and granted a waiver of informed consent.

Participants. Data are from households that participated in a pilot programme administered by a southwestern US electric utility. The utility sent invitations by direct mail and email soliciting opt in to the 2016 TOU pilot to roughly 197,000 households, 14% of which opted in. Some households that accepted the offer were not enrolled because they were ineligible (for example, were already participating in a special rate programme). The utility randomly assigned 21,534 households to either TOU1 ($n = 4{,}709$), TOU2 ($n = 6{,}365$), TOU3 ($n = 3{,}746$) or the control group that opted in to TOU but was not placed on a TOU rate ($n = 6{,}714$). Low-income households and those with elderly members were deliberately oversampled for TOU2. TOU3 was not fully rolled out by the start of the study period, due to additional complexities unique to the rate, and so could not be included in the present study; we consider only TOU1, TOU2 and the control group.

TOU pilot. Households assigned to a TOU rate were shifted to this new rate in June or July of 2016 and remained on these rates for a full year. The period of the pilot covered by this study occurred in the summer, specifically the months July–September 2016. Owing to the geographical region, the weather would have been warm to hot and mostly lacking precipitation for the majority of the sample.

After the rate assignment, participants received information letters. Those in the control group received a welcome letter informing them that they would remain on their current rate. TOU participants received a letter containing information on their TOU rate plan and bill protection (if customers paid more on TOU at the end of the 12-month pilot than they would have under their previous plan, the utility would credit back the difference after the pilot ended). They also received TOU time-period stickers, conservation-reminder stickers and door hangers with recommended seasonal thermostat settings.

TOU1 and TOU2 on-peak times covered different hours depending on weekend versus weekday. On-peak hours were in the evening. Cost per kilowatt hour varied depending on the rate and season. Summer rates per kilowatt hour for TOU1 were ¢23 for super off-peak, ¢27.61 for off-peak and ¢34.51 for on-peak. Summer rates per kilowatt hour for TOU2 were ¢17.33 for super off-peak, ¢29.3 for off-peak and ¢53.26 for on-peak. TOU1 had six hours on-peak from 14:00 to 20:00 for summer weekdays and no on-peak times at weekends. TOU2 had three hours on-peak from 17:00 to 20:00 for summer weekdays and no on-peak times at weekends.

Households could earn up to US$200 as compensation for their participation, given as bill credits; US$100 at enrolment and US$50 after completing each of two surveys. The second survey, which we do not have data for due to the timing of our data request from the utility, was administered in the summer of 2017.

Survey. Customers were first surveyed between October and December 2016. At this point, TOU participants had 3–6 months' experience with TOU rates, solely or primarily in the summer. Survey response rates were 82% overall, out of the 18,747 households that remained in the pilot by December 2016 after being enrolled and not being dropped out of the pilot due to relocating, ineligibility or choosing to leave. For the full sample examined in this manuscript ($n = 7{,}487$), 85% responded by email, 11% by mail and 4% by phone.

Electricity use data. Our participants experienced the TOU pilot during the summer months. Thus, the analyses use hourly electricity use data for each household only during the summer months (July, August and September) for the baseline years 2014 and 2015, and for the pilot year of 2016. Summer hourly consumption data were used to form the 'on-peak use' variable (kilowatt hours, daily mean).

In forming the 'on-peak use' variable, we took into account the different lengths of on-peak time, that is, TOU1 on-peak sums the use during the 6 h on-peak, and TOU2 on-peak sums the use during the 3 h on-peak. Control group households were all coded for both hypothetical TOU1 and TOU2 rate structures, and on-peak use was defined as use that happened during the hours designated as on-peak by that rate. In each analysis, the full control group is compared to either TOU1 or TOU2, using the corresponding on-peak hour coding for control groups to generate the change in on-peak use variable used for analysis. 'Change in on-peak use' between the baseline and TOU pilot years is taken as the TOU pilot daily on-peak mean use minus the mean baseline on-peak use. The following equation describes the change in on-peak use calculation: $\Delta U = [U_{2016} - (U_{2014} + U_{2015})/2]$, where U represents the mean daily on-peak use in kilowatt hours in each year.

Electricity bills. As for use, the billing data for each household were examined only for July, August and September for the baseline years 2014 and 2015, and for the pilot year 2016. Bill amounts used for the analysis were actual bills that customers received. That is, they reflect the true amount customers paid each month. All the households kept for analysis had billing data for at least two of the three summer months. Mean monthly bill size was taken as the mean of bills across July, August and September for a given year. A baseline bill variable was created by taking the mean of the 2014 and 2015 bills, and the pilot bill was the 2016 mean bill. A 'change in bills' variable was created by subtracting the baseline bills from the pilot bills using the equation: $\Delta B = [B_{2016} - (B_{2014} + B_{2015})/2]$, where B represents mean bill amounts in US dollars each year.

Climate zone. Climate zones are defined by a government agency, and are matched to each household based on the household's location. The government agency bases climate zone boundaries on the household energy use expected for heating and cooling, local temperature and local weather, among other factors. There are eight climate zones covered by households in our sample.

Survey and vulnerability measures. The survey assessed a number of demographic characteristics, which included respondent age and ethnicity/race, and household member disabilities. It also assessed homeownership status and educational attainment, the former of which is included in regression models due to the expectations that homeowners would more easily be able to upgrade appliances and building insulation to increase energy efficiency. Homeownership was coded as a dichotomous variable with 1 indicating homeownership and 0 indicating otherwise.

We defined vulnerability indicators as follows:

- Low income. Enrolment in an electric utility financial aid programme (that gives households discounts on electricity bills if income falls below certain limits based on the number of household members) serves as an indicator of low income, with those enrolled in a financial aid programme coded 1 and others coded 0. Enrolment status was provided by the utility.
- Elderly. The survey assessed respondent birth year with an open entry. It additionally asked: "How many people in each of the following age categories lived in your home this summer, not including yourself?", with response categories including "Between 65 and 74 years old", "Between 75 and 84 years old" and "85 years or older". Responses to this question and birth year were aggregated to determine whether anyone over 65 resided in the household. If someone over 65 years old lived in the household, that household was coded 1. Otherwise, it was coded 0.
- Young children. Respondents were asked "How many people in each of the following age categories lived in your home this summer, not including yourself?" with the youngest category being "Under 6 years old". Households that had at least one member under 6 years old were coded '1' for young children, otherwise households were coded 0.
- Disability. If someone answered yes to either "Does anyone in your household have a disability or serious medical condition that requires your home to be cool in the summer?" or "Does anyone in your household have a disability or serious medical condition that requires them to use more energy for medical equipment?", that household was coded 1. Otherwise, it was coded 0.
- Hispanic. Race and ethnicity were assessed using the question "Which categories describe you?", in response to which households could mark as many options as they chose to out of the list provided. If a respondent identified as "Hispanic, Latino, or Spanish origin", their household was coded 1 for the Hispanic indicator. If a household marked "White" as a category that described them, and did not mark any other category (including, but not limited to, "Hispanic, Latino, or Spanish origin"), then they were coded as 0. That is, households were only coded 0 if they identified as white alone. Other households (for example, those that identified as African American, Asian American, American Indian and so on) could not be considered

non-vulnerable in terms of ethnicity/race, so were treated as missing. Thus, all analyses using the Hispanic vulnerability indicator use a subsample ($n=4{,}925$), and the Hispanic indicator is not included as a control in other analyses.

- African American. Coding follows the procedure described for the Hispanic indicator. If the respondent identified as "African American", their household was coded 1 for the African American indicator. If a household marked "White" as a category that described them, and did not mark any other category (including, but not limited to, "African American"), then they were coded as 0. All analyses using the African American vulnerability indicator use a subsample ($n=3{,}970$), and the African American indicator is not included as a control in other analyses.

AC curtailment and ownership. AC curtailment was assessed by asking respondents, "Since the beginning of this summer, how often, if at all, did you take the following actions to reduce your household's electricity use in the afternoons and evenings?—Turned off air conditioning" on a 5-point Likert scale where 1 = Never and 5 = Always, with an additional option of 6 = Not applicable. We retained those who answered "Not applicable" within the sample, but coded these respondents as missing when conducting analyses that make use of the curtailment scale.

The survey assessed both the reported behavioural curtailment of AC and the presence of AC technology. Households were considered to have AC if they had central AC, window AC, evaporative coolers or heat pumps (which are capable of providing AC). Some households gave conflicting answers to their curtailment of AC and their ownership of AC technology; for example, some households rated their curtailment of AC rather than selecting "Not applicable", but indicated that they did not own AC technology. Households were coded 0 for AC ownership if they chose "Not applicable" for AC curtailment and also indicated they owned no AC technology, and were coded 1 for AC ownership if they rated their AC curtailment (that is, did not choose "Not applicable") and additionally indicated that they owned a form of AC technology. Households that gave conflicting answers were dropped ($n=850$).

Measures for discomfort and medical needs. Discomfort was assessed with responses to the question "Since June 2016, how often, if ever, were you or any members of your household uncomfortably hot inside your home because you were trying to save money on your electricity bill?" on a 5-point Likert scale with 1 = Never and 5 = Always.

The need for medical attention was assessed with responses to the question "Since June 2016, about how many times, if ever, did you or any members of your household need medical attention because it was too hot inside your home?", with respondents able to choose between options of "Never", "1", "2", … to "more than 10". A dichotomous variable was created, with respondents coded 1 if they answered that they had needed medical attention at least once, and 0 otherwise.

Dropped participants. By December 2016, 2,787 households had dropped out of the pilot due to relocating, ineligibility or choosing to drop out, which left 18,747 households enrolled. Of these, 16,181 households responded to the survey. Before receipt by the authors, the utility removed respondents who answered 5.4% or less of the survey items. Respondents were also removed if they provided the same rating for all items across any of the three multi-item measures in the survey (for example, if a participant gave ratings of '4' to all the items in one multi-item question). Additionally, respondents were removed if they selected all the items in a 'select-all-that-apply' question in which some categories were mutually exclusive, for example, if when asked "What kept you from shifting use in the evening" respondents selected both "Nothing keeps me from shifting my use" and "My schedule doesn't allow me to reduce my usage".

This yielded a sample of $n=16{,}073$ households, with 5,198 in the control group, 3,522 on TOU1 and 4,593 on TOU2; the 2,760 households on TOU3 were not used, which left an initial sample of $n=13{,}313$ households. Additional households were then dropped for the reasons below.

First, households that were missing electricity use data on any days in July, August and September in 2014, 2015 or 2016 were dropped. A total of $n=1{,}339$ households were dropped due to incomplete use data; the missing values were predominantly clustered across several days or weeks at the beginning of the recorded period, which indicates that either no account was established for that address (that is, residents moved in during the study period) or the house did not have a smart meter at the beginning of the time period.

Second, billing outliers were removed. Customers with baseline or pilot period use below the 1st percentile or above the 99th percentile were dropped from the sample ($n=341$ households).

Third, households with incomplete survey data were dropped. Households were dropped if they had not answered the AC curtailment question, if they had not answered the question assessing the presence of AC, if they had not answered each vulnerability indicator (excepting the race/ethnicity indicators, which used subsamples), if they had not answered both the discomfort and the medical attention questions and if they had not included an answer to homeownership ($n=3{,}296$).

Finally, households that gave conflicting answers to their curtailment of AC and their ownership of AC technology were dropped ($n=850$). Our final sample comprised 7,487 respondents.

Dropout analyses. The utility with which we partnered provided data only for those who at least partially completed the survey, so we are unable to evaluate presurvey opt outs. We used a two-tailed t-test to understand whether there was a systematic difference regarding the change in bills from baseline to pilot year between households that completed the survey and those that did not complete the survey, restricting the sample only to those who had complete billing and use data ($n=11{,}633$); among those with incomplete billing and use data, this incompleteness was due to factors beyond the households' control, such as the installation of smart meters. We found that survey completers ($n=7{,}487$) saw larger bill increases (baseline to pilot, simple difference) than non-completers ($n=4{,}146$); $M_{\mathrm{complete}}=16.09$, $M_{\mathrm{non\text{-}complete}}=13.35$, $P=0.003$, $d=0.06$. We additionally used a two-tailed t-test to examine the systematic difference in change in on-peak use from baseline to pilot ($n=11{,}633$) for both TOU1 peak-time survey completers (TOU1 + control, $n=4{,}869$) versus non-completers (TOU1 + control, $n=2{,}688$) and TOU2 peak-time survey completers (TOU2 + control, $n=5{,}483$) versus non-completers (TOU2 + control, $n=3{,}107$), and found no difference between completers and non-completers in usage reduction ($M_{\mathrm{complete,TOU1}}=-0.11$, $M_{\mathrm{non\text{-}complete,TOU1}}=-0.11$, $P=0.91$, $d=0.002$; $M_{\mathrm{complete,TOU2}}=-0.11$, $M_{\mathrm{non\text{-}complete,TOU2}}=-0.09$, $P=0.56$, $d=0.01$). We finally examined differences in baseline use ($n=11{,}633$) between those who completed the survey ($n=7{,}487$) and those who did not ($n=4{,}146$), and found that completers had a higher daily baseline average use ($M_{\mathrm{complete}}=24.98$, $M_{\mathrm{non\text{-}complete}}=22.43$, $P=0.000$, $d=0.18$). In summary, those who completed the survey had higher baseline use and larger bill increases during the pilot than the non-completers. The effect size of the baseline difference in daily average use between the survey completers and non-completers is large, whereas the effect size difference in billing is small.

We further considered dropout across different conditions due to survey missing data: of 4,514 in the control group, 37% were non-completers, compared to 34% of the 3,043 on TOU1 and 36% of the 4,076 on TOU2. A simple logit model was used to estimate the correlation of group assignment with the likelihood of having incomplete data. We first considered all three rate types using dummy variables (with the control as baseline), and found that, compared to the control, TOU1 is associated with a higher likelihood of incomplete data ($P<0.034$), but TOU2 is not ($P<0.464$). We then considered only TOU1 versus TOU2, with TOU1 as the baseline, and found no difference in association with non-completion ($P<0.155$). Finally, we used a simple logit to consider whether vulnerability predicts non-completion of the survey. We found that low-income ($P<0.001$), elderly ($P<0.001$), disability ($P<0.001$), Hispanic ($P<0.001$) and African American ($P<0.011$) groups were all less likely to complete the survey compared to the respective non-vulnerable counterparts.

Difference-in-difference-in-differences analyses. The difference-in-difference-in-differences billing analyses are described by the equation:

$$\begin{aligned} B_{\mathrm{st}} = {} & \beta_0 + \beta_1 \mathrm{TreatR1_s} + \beta_2 \mathrm{Post_t} \\ & + \beta_3 \mathrm{Vulnerable_s} + \beta_4 (\mathrm{Treat_s} \times \mathrm{Post_t}) \\ & + \beta_5 (\mathrm{Vulnerable_s} \times \mathrm{Post_t}) + \beta_6 (\mathrm{Vulnerable_s} \times \mathrm{Treat_s}) \\ & + \beta_7 (\mathrm{Vulnerable_s} \times \mathrm{Treat_s} \times \mathrm{Post_t}) + \varepsilon_{\mathrm{st}} \end{aligned}$$

where B_{st} is the mean monthly bill amount (US dollars), $\mathrm{TreatR1_s}$ is a dichotomous variable set to 1 if the household was on TOU1 and 0 if the household was in the control group, $\mathrm{Post_t}$ is a dichotomous variable set to 1 if the year was 2016 and 0 for the baseline indicator (the mean for the 2014 and 2015 mean monthly bills amount is taken to form the baseline indicator), $\mathrm{Vulnerable_s}$ is the indicator for vulnerability set to 1 if the household is vulnerable on a given indicator and 0 if it is not vulnerable on that indicator (see the descriptions above for the coding of vulnerable groups). These terms are included as controls for each individual indicator. Subscript s refers to a term that differs across subjects, but is constant over time for a given subject. Subscript t refers to a term that changes over time, but is constant across subjects at any given point in time. Terms with sub-script st vary across both subjects and time. $\mathrm{Treat_s}\times\mathrm{Post_t}$ controls for the effect on bills due to the assignment to the TOU rate during the pilot year, and takes a value of 1 for households that were on TOU in the pilot year and 0 for all others; $\mathrm{Vulnerable_s}\times\mathrm{Post_t}$ controls for differences experienced during the pilot year by vulnerable groups regardless of the rate assignment, and takes a value of 1 for vulnerable households during the pilot year and 0 for all others; $\mathrm{Vulnerable_s}\times\mathrm{Treat_s}$ controls for the differences of vulnerable groups assigned to the TOU condition regardless of whether the pilot had begun or not, and takes a value of 1 for vulnerable households assigned to a TOU rate and 0 for all others. The term of interest is $\mathrm{Vulnerable_s}\times\mathrm{Treat_s}\times\mathrm{Post_t}$, which gives the effect of the TOU assignment during the pilot year on vulnerable groups; vulnerable households assigned to a TOU rate have a value of 1 for this term during the pilot year; all other groups, and other time periods, take a value of 0. Errors are clustered at the household level. $\varepsilon_{\mathrm{st}}$ refers to the idiosyncratic error term.

The same form is used to examine TOU2, with $\mathrm{TreatR2_s}$ (a dichotomous variable set to 1 if the household was on TOU2 and 0 if the household was in the control group) substituted for $\mathrm{TreatR1_s}$. Likewise, this form is used to examine the on-peak usage differences between groups and time periods, with the dependent variable being on-peak use (kilowatt hour, mean) instead of the monthly bill amount.

Regional fixed effects regression. We used regional fixed effects analyses to consider the impacts of predictor variables on billing, discomfort and the need for medical attention. By using regional fixed effects grouped by climate zone, these models control for unobserved time-invariant differences between households, for those differences associated with living in different climate zones. That is, the predictions of respective dependent variables in each regional fixed effects analysis are estimated conditional on the climate zone, and each climate zone is associated with a unique intercept.

AC curtailment analysis. We used a subsample of $n = 4,129$ households that were assigned to TOU (not control) and did not answer "Not applicable" when asked about AC curtailment (that is, we only considered households that have access to AC in their homes). Only households assigned to TOU were examined to restrict the comparison to households with the incentive to curtail during peak hours. For this subsample, we examined whether the vulnerable or non-vulnerable groups reported more frequent curtailment in the form of AC use. We used Wilcoxon rank sum tests (due to non-normal distributions) to test for differences in the reported frequency of evening AC curtailment among vulnerable versus non-vulnerable households. Table 4 reports the means, z scores with associated P tests and Cohen's d effect sizes (d). Effect sizes indicate the importance of mean differences; a large effect size is >0.8, a medium one >0.5 and a small one >0.2 (ref. [61]). The results provide a richer description of how households responded to TOU rates, and are correlational rather than causal.

Online content. Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41560-019-0507-y.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The processed or aggregated data that support the plots within this paper and other findings of this study are available from the corresponding author upon reasonable request. Authors signed a non-disclosure agreement with the utility that provided the data analysed in this paper, and under this agreement are unable to make the raw data publicly available. Source data for Fig. 1 are provided with the paper.

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Author contributions
Both authors conceived the paper and designed the research. L.W. designed the analysis methods, performed the analyses and wrote and revised the paper. N.S. reviewed several drafts and made revisions.

Competing interests
The authors declare no competing interests.

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	The study is quantitative
Research sample	The study used an existing dataset provided by a utility in the US that has asked to remain anonymous. The sample is all from a single US state. The sample contained opt-in participants, and may not be completely representative of the general population.
Sampling strategy	The sample included individuals who opted in to a utility pilot program. These individuals were then randomized to one of four conditions, including a control group.
Data collection	Some of the data is usage and billing data provided directly by the utility. The rest of the data is survey data collected by the utility; for the full sample examined in this manuscript (n = 7487), 85% responded by email, 11% by mail, and 4% by phone.
Timing	Survey data was collected October-December 2016; usage and billing data are recorded from 2014-2016.
Data exclusions	Participants in one of three utility treatment groups were not included due to that treatment having unusual features. Participants were also excluded if they had incomplete billing, usage, and survey data, leaving 7487 of the 16181 that had remained in the pilot program and completed the survey.
Non-participation	2787 households dropped out of the pilot due to relocating, ineligibility, or choosing to drop out, leaving 18747 households enrolled. Of these, 16181 households responded to the survey.
Randomization	Participants were randomly allocated to a treatment or control condition

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Population characteristics	See above
Recruitment	Participants opted-in to a utility pilot. Thus, the sample may contain participants who are more favorable to this type of rate program than the general population.
Ethics oversight	The University of Southern California's University Park Institutional Review Board reviewed and approved this research, and granted a waiver of informed consent.

Note that full information on the approval of the study protocol must also be provided in the manuscript.