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Exploring household energy rules and activities during peak demand to better determine potential responsiveness to time-of-use pricing

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ABSTRACT

The success of time-of-use (TOU) pricing, where consumers are charged higher rates during peak usage windows, depends on consumer flexibility—an assumption that may not be true for all households or activities. We draw on concepts from social practice theory to explore the flexibility of residential electricity consumption, examining both household rules that govern energy conservation and activities that comprise the peak demand period. Surveying 337 households in a Northern California city slated for TOU rates, our goal was to better understand household energy rules and peak activities; willingness-to-shift peak activities; and relationships between household rules, willingness-to-shift and electricity usage. While respondent demographics and estimated monthly electricity bill (our proxy for usage) were associated with following energy rules, motivations for following rules (e.g., environmental, monetary) dominated. For respondents' willingness-to-shift peak activities, square footage, number of household members, and smart technology were important, along with energy rule participation and the number of peak activities. Energy rule participation was also associated with lower bills, while number of household members and peak activities were associated with higher bills. Our findings provide insights into pathways for modifying energy use during peak to allow for easier integration of renewables into the grid.

1. Introduction

The mismatch in timing between renewable energy production and electricity consumption is one of the largest obstacles to a renewable energy transition. Maximum solar production, for example, typically occurs midday when overall grid demand is generally low (Jones-Albertus, 2017). Current limitations in storage technology and capacity prevent solar-generated electricity from being stored earlier in the day and then discharged in the evening during peak demand, forcing utilities to ramp up traditional fossil fuel-burning plants—at higher marginal costs—to meet consumer demand (Harding and Sexton, 2017). Consequently, demand side management programs aimed at shaving and shifting peak demand have been the focus of considerable research (Lund et al., 2015).

The residential sector is a frequent target for demand side management programs (Sorrell, 2015), with the adoption of alternative electricity pricing structures often at the center of policies designed to reduce peak household electricity consumption (Shi et al., 2020). However, most residential customers in the U.S. pay the same rate for electricity consumed regardless of current grid conditions (Harding and Sexton, 2017). New policy proposals, made possible by the implementation of advanced metering infrastructure, incorporate variable rates, including time-of-use (TOU) pricing. TOU pricing charges consumers more per kilowatt-hour consumed during a specified peak time period, thus encouraging consumers to save or shift their consumption to off-peak time periods.

The success of TOU pricing depends on consumer flexibility and responsiveness to price changes—an assumption that may not be true for all households or energy-consuming activities. Unlike in commercial and industrial sectors, residential customers have little experience with TOU pricing. Moreover, results from decades of TOU pilot studies have been inconsistent, with a large range of estimated elasticities (i.e., price elasticity of demand or the degree to which consumers change their demand for electricity in response to changes in price) (Aigner, 1985; Jessoe and Rapson, 2014; Harding and Sexton, 2017).

Instead of focusing on price elasticity to assess the flexibility of

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residential electricity consumption, we draw on concepts from social practice theory and focus on the rules, activities and practices that underpin household energy usage, particularly during the peak period, and how these factors relate to overall usage. To do so, we conducted a survey of 337 households in a Northern California city slated to transition to TOU rates. We focused on household rules related to energy use (e.g., keeping doors/windows closed while the AC or heat is on) *and* the performance and flexibility of energy-consuming activities (e.g., taking showers/baths, washing dishes) during the peak period. Our goal was to better understand household energy conservation rules and peak activities; willingness-to-shift peak activities; and relationships between demographic and home characteristics, household rules, willingness-to-shift and electricity usage.

1.1. Time of use (TOU) electricity rates

The concept of variable electricity pricing is not new; TOU rates were first proposed more than a century ago (Clark, 1911). Current interest in TOU rates has been driven primarily by increased solar power generation, including distributed generation from residential rooftop solar panels (Hledik et al., 2017). In 2013, the California Independent System Operator (ISO) highlighted the gap in timing of solar generation and electricity demand, predicting that the uptake of solar panels connected to the grid would widen this gap substantially and lead to potential issues in energy production ramping and overgeneration (California ISO, 2016). While this gap was initially considered a future concern, it has already begun to present challenges for the California energy system (Golden et al., 2019). In 2015, the California Public Utilities Commission announced plans to implement state-wide default TOU rates in 2018—a deadline that has since been pushed back (Trabish, 2018)—to better manage the state's energy demand issues. California's adoption of TOU rates is a major policy breakthrough for TOU rates and would set a new standard (Prabhakaran and Dome, 2015).

Most TOU plans have two time periods (peak and off-peak), with a median price differential from peak to off-peak of 2.7-to-1, equivalent to a median price gap of 10 cents per kilowatt-hour (Hledik et al., 2017). The duration of the peak window varies from 2 to 13 hours, with more recently developed rates having peak periods of 6 hours or less. In our community of interest at the time of our survey (June–August 2018), the local utility (Pacific Gas & Electric or PG&E) had three primary TOU rate plans customers could opt-in to. All three plans featured two prices (peak and off-peak) covering a 5-hour peak period (3pm–8pm or 4pm–9pm); two plans covered only weekdays, while the third applied to every day. Each plan had different summer (June through September) and winter (October through May) rates, with the summer period having a larger price differential than winter (PG&E, n.d.). PG&E's TOU rates were thus similar to national averages in terms of pricing periods and peak window length but with a lower price differential of between 1.2-to-1 and 1.4-to-1.

2. Literature review

2.1. Critiques of TOU rates and social practice theory

Mechanisms to influence consumer behavior originating from the field of economics, specifically that consumers respond to price incentives, serve as the bedrock for variable electricity rates like TOU pricing (Houthakker, 1951). Consumers are assumed to have rational preferences, maximize utility, act on all relevant information, and therefore change energy use behaviors in response to a change in energy pricing (Faruqui et al., 2017). However, social scientists who study residential energy usage from fields outside of economics have questioned if economic theory is the appropriate lens through which to view the issue of demand reduction (Lutzenhiser, 1992; Boudet et al., 2016; Boudet, 2019; Strengers, 2019; Sovacool, 2014; Higginson et al., 2015). These researchers have called for a stronger consideration of non-economic social sciences in energy studies, as the analysis of economists often fails to address non-monetary mechanisms for encouraging changes in energy consumption.

Electricity is often used to fulfill specific household needs, desires and practices, such as lighting, cleanliness, comfort and nourishment (Shove, 2003; Sorrell, 2015); the meter merely tracks the running tally of a household's usage. The relationships between household activities *and* reduction during a TOU pricing window are complex. For example, a 10% reduction in peak use does not directly translate into a 10% reduction in lighting or comfort. Rather, a reduction in peak use may entail using appliances and devices more efficiently, shifting bundles of activities like laundry out of the peak usage period, and/or altering household members' perceived needs during peak (e.g., by fulfilling entertainment needs via outdoor recreation or reading instead of watching TV). Yet, we know from previous studies that the knowledge and skills needed to drive these reductions are often lacking. For example, Attari et al. (2010) found that people have little actual knowledge about the precise energy usage of activities and the savings that would be realized through different behaviors, implying that residential consumers may struggle to connect activities and savings. Similarly, White and Sintov (2018), examining a TOU pilot program, found that perceptions of savings were the best predictor of intent to remain in the TOU program, yet such perceptions were only weakly linked to actual savings. The idea that demand reduction is understood better if the unit of analysis is the actual energy-using activities, rather than kilowatt-hours used, has emerged primarily from the increased application of social science theories from psychology and sociology to energy conservation. Here, we draw on concepts from one such theory: social practice theory.

Social practice theory—a form of cultural theory that focuses on practices as the core unit of analysis (Reckwitz, 2002)—has only recently been applied to matters of energy (Shove and Walker, 2014), but its application is growing rapidly (Higginson et al., 2015). Reckwitz describes a practice as "a routinized type of behavior which consists of several elements" (p. 249). Strengers (2012) identifies four main elements of social practices: "*common understandings* about what the practice means and how it is valued, *rules* about what procedures and protocols must be followed and adhered to, *practical knowledge* about how to carry out and perform a practice, and *material infrastructure*—or the 'stuff' that makes the practice possible, sensible and desirable" (p. 228). Practices evolve, come into existence, and disappear over time as the links between elements are made and broken. Energy-using practices derive from multiple sources, e.g., the availability of appliances like dishwashers, clothes dryers and AC to provide particular services (Jack, 2017); changing cultural expectations of comfort in buildings (Chappells and Shove, 2005); shifts in household needs as household members enter, exit and age (Strengers et al., 2016).

Shove (2010) identifies social practice theory as a valuable perspective for energy consumption due to the failures of both economic incentives *and* standard models from social psychology of individual behavior in promoting energy conservation and reducing climate change impacts. The so-called "ABC" model—the notion that individuals form attitudes, which inform their behaviors, that ultimately dictate the choices they make—assumes a causal relationship between attitudes and behavior, i.e., changing attitudes can change behavior. Strengers (2012) expanded this "ABC" model with an additional "D" for demand, as the same theory that underpins much of demand management policy. Strengers (2012) likened the ABCD theory to expecting individuals to act as miniature utility companies in how they schedule their energy consumption. Yet, in the context of household electricity usage, electricity itself is only one element of the social practices that occur within the household (Shove et al., 2012; Shove and Walker, 2014). The social practice theory perspective has prompted research applications that explore residential energy use by focusing on the meanings, conventions and routines that comprise total energy consumption and how these may shift over time. In this research, in addition to investigating energy-using activities (as opposed to energy usage), we study household rules as an operationalization of conventions and routines. The household rules that govern energy-using activities, as an element of social practice, have received little scholarly attention.

Moreover, we explore these energy activities and rules through survey research, as opposed to the prevailing qualitative approaches applied to date (Higginson et al., 2015), and connect them to a measure of overall household energy usage—reported average monthly bills. Survey-based investigation allows for both larger and more representative samples of respondents for analysis, as well as the ability to quantitatively test associations between respondent characteristics, reported energy-using rules, peak energy-using activities, flexibility in the peak period, and overall energy use. More quantitative approaches like the one we take here are often a natural follow-on in human behavior studies to the more discovery-focused qualitative methods previously applied in the context of social practice theory.

2.2. Research questions

As an important element of social practices, we first investigate the level of participation with household energy conservation rules and factors (e.g., respondent demographics, home characteristics, motivations, overall household energy use) associated with rule participation.

RQ1: What household energy conservation rules do respondents report govern energy use?
RQ2: What factors shape participation in household energy conservation rules?

Scholars have repeatedly found turning out the lights to be one of the most popular energy conservation actions (Kempton et al., 1985; Attari et al., 2010; Lundberg et al., 2019), so we expect that this rule will be prevalent among our respondents. Yet, little is known about what household or demographic factors shape household rules, so we see our work here as mainly exploratory.

Regarding peak activities, Shove and Cass (2018) note that the first step to understanding the timing of energy demand is to discover what people are using electricity for in the peak period. To investigate this proposition, we incorporated the following research questions:

RQ3: What energy-using activities do respondents report performing in the peak period?
RQ4: What energy-using activities do respondents report being willing to shift out of the peak period?

Both existing literature and our previous qualitative research (Mauriello et al., 2019) informed our predictions regarding peak energy-using activities and willingness-to-shift. The timing of the peak period—defined here as 3pm to 9pm—coincides with when most people prepare and eat the evening meal, so we would anticipate respondents to indicate the use of electricity for cooking purposes. The time period also overlaps with when people commonly return home from work, so leisure activities, such as watching television and using a computer would likely to be performed by a high proportion of respondents during the peak period. For example, Powells et al. (2014) explored the likelihood of households to perform (and flexibility to shift) a variety of cooking, entertainment, cleaning, and bathing practices during the peak demand period. Through over 100 interviews with UK households, they found that dining and television watching were the most commonly occurring but least flexible practices they examined. Others, such as Smale et al. (2017), Ozaki (2018), and Öhrlund et al. (2019), similarly found a high performance of cooking and leisure activities in households during peak, with cleaning activities being performed somewhat less frequently. Moreover, Ozaki (2018) and Öhrlund et al. (2019) also found that some activities—such as cooking dinner and watching television—were too firmly rooted in the peak period to be shifted, regardless of the price incentive, whereas others, such as cleaning practices (e.g., laundry), had higher perceived flexibility. Consequently, we expected that we would find an overall high performance of leisure and cooking activities during peak but a low willingness-to-shift such activities. In contrast, we expected a higher willingness-to-shift cleaning activities like laundry and dishwashing.

Building on previous research, we also sought to determine what household and demographic factors shape demand flexibility:

RQ5: What factors shape willingness-to-shift peak activities?

Empirical research by sociologists and psychologists has looked at demographic differences in energy usage and activities. For example, researchers have repeatedly highlighted the importance of household size, composition, and income in shaping overall household energy use (Abrahamse and Steg, 2011; Wilson and Dowltabadi, 2007; Lutzenhiser, 1993). We anticipated similar factors to be related to willingness-to-shift activities.

Similar household and demographic factors have been highlighted by social practice theorists. Strengers et al. (2016) noted that a reasoned action approach assumes that the consumption of energy for specific purposes can be automated and controlled through smart technology yet fails to account for so-called “dumb” energy users, such as children, pets, and inanimate objects (762). They went on to illustrate the ways in which pets can account for additional household energy usage, such as the need for heating or cooling to meet thermal comforts. Similarly, Nicholls et al. (2015) emphasized how the transition to parenthood changes the meanings of practices, such as cooking and entertainment. Exploring the heterogeneity of flexibility across different types of households, Torriti et al. (2015) found that those households with children were less flexible in their ability to shift activities during peak demand. However, the relationship between children and inflexibility is not universal, as Friis and Haunstrup Christensen (2016) found no such connection between shifting activities and household size through interviews with Danish households experiencing variable pricing rates. In fact, Friis and Christensen found that households with small children had greater flexibility due to increased awareness of their daily schedules and the need to be adaptable. Therefore, it is possible that the composition of the household affects the energy-using practices performed but in ill-defined contexts, and perhaps fluctuating and heterogenous, ways.

An additional household-level characteristic that may be important is technology in the home. The ability to use technology to automate home appliances has been identified as critical to demand flexibility from economic and engineering perspectives, but the social practice perspective has mixed views. Ozaki (2018) found interviewees hoping for more automation from appliances that would “make life a lot easier” (p. 15). Higginson et al. (2014), conversely, contended that automating resource management may distance people from the resource and therefore be less effective. Strengers (2014) has written extensively on the disconnect between the energy industry’s vision of smart energy consumers—“Resource Men” who are expected to fully leverage the available data and technology to make rational consumption choices—and the realities of how consumers engage with their energy usage. The assumption of many utilities is that having smart technology in the home, combined with the availability of personalized energy data and variable pricing, will prompt behavior change to reduce overall usage and/or encourage shifts in energy-using activities outside of TOU. However, according to Strengers (2014), these strategies are based on a limited understanding of human nature and may even result in more energy-intensive practices that negate savings. While we are unable to directly measure energy use either within—or outside—TOU, we are able to estimate total energy use within the home, prompting us to ask:

RQ6: What factors, including use of smart technology, are related to a household’s total energy use?

We therefore investigate the role of demographics (e.g., age, gender, race, income, education), home characteristics (e.g., household size, ownership, square footage, smart technology), and motivations in shaping household energy rules, willingness-to-shift activities out of peak, and overall energy use.

3. Methods

3.1. Survey sample

For this research we selected a community in Northern California located in Alameda County, less than 30 miles from Oakland and San Francisco, with a population of 226,551, to draw our survey sample. This community, encompassing the city of Fremont and surrounding area, is diverse and economically thriving with a strong commitment to environmental sustainability, and, with its high adoption of residential solar and electric vehicles, is well suited for understanding attitudes toward emergent energy issues (Kelly, 2018). To recruit participants, we used a convenience sample of respondents provided through Qualtrics ™, an internet-based survey research company. To recruit within our sampling frame, respondents were first screened by ZIP Code and included Fremont-area ZIP Codes (94536, 94537, 94538, 94539, 94555, 94560, and 94587) as well as ZIP Codes with coverage in neighboring Union City (94544 and 94552). The survey was administered from June to August 2018 resulting in 337 valid responses[1] with the questionnaire designed to gain an understanding in three key areas: (a) rules around energy use within the home, (b) peak energy-using activities and (c) willingness-to-shift peak activities.

Compared to the 2017 American Community Survey 5-year estimates (ACS) for the Fremont subdivision of Alameda County (U.S. Census Bureau, n.d.), our sample had a higher level of educational attainment (66% vs. 46% having a bachelor's degree or higher), was older (median age of 48 vs. between 35 and 44), and had a larger proportion of white respondents (35% vs. 25% identifying as white only). Our survey respondents also had a similar proportion of women (53%) compared to ACS estimates (51%), while reported income (between $100,000 and $149,000) was consistent with this area's income estimates from the ACS ($112,467 median household income).

3.2. Variable operationalization and measurement (Table 1)

3.2.1. Household energy rules

To gain an understanding about conventions that govern energy use in the home, survey respondents rated their level of participation in the following energy conservation rules: "Keep doors/windows closed when AC or heat is on"; "Turn off the TV when you are the last person to leave a room"; "Turn off the lights when you are the last person to leave a room"; "Fill the dishwasher to capacity before washing"; "Wait to wash laundry until you have a full load"; "Don't put hot food in the fridge"; "Close the refrigerator or freezer door quickly when taking out food"; "Close the drapes or shades to keep home cool/warm"; "Wear warm clothes to use less heat"; "Turn off household computers when not in use"; "Do laundry in cold rather than warm or hot water"; "Turn off power strips when not in use"; "Dry clothing on clothes line, rack or hangers instead of in the dryer"; "Take showers that last 5 min or less"; and "Turn off the oven 10 min early". We asked participants "To what extent do you and members of your household follow these rules," with response categories oriented on a 5-point scale from 1 = "Not a rule" to 5 = "All of the time." Furthermore, for applications in analysis, these 16 rules were combined into a single mean composite index with acceptable reliability (Cronbach's alpha = 0.815), which we refer to as the *energy rules index* (mean = 3.695; SD = 0.602).

3.2.2. Motivations for household energy rules

We also considered respondent motivations for following these energy rules, asking participants "How important were the following factors in determining these household rules", with items "Saving money", "Saving the environment", "Teaching members of my household (children, etc.) responsibility", and "Avoiding wastefulness" situated on a 4-point scale from "1 = Not at all important" to "4 = Very important." We apply single energy savings rule motivation items, as well as form a mean composite index, which we refer to as the *rules motivations index* (mean = 3.413; Cronbach's alpha = 0.700), in our analytical approach.

3.2.3. Peak energy activities

To assess energy-using activities during the peak demand period, respondents were asked, "Which of the following household activities do you or members of your household regularly perform on weekdays from 3pm to 9pm?" with response categories[2]: "Use the washing machine"; "Use the clothes dryer"; "Cook with stovetop/range or oven"; "Run the dishwasher"; "Take showers"; "Take baths"; "Use electric heating (when it's cold)"; "Use a fan or AC (when it's hot)"; "Use a computer, game console, or tablet"; "Use a television"; "Turn on lights"; and "Charge plug-in electric vehicle[3]". Total counts of activities respondents reported performing during the peak period ranged from 1 to 11 activities (out of 12 total possible activities) (mean = 6.6, SD = 2.3).

3.2.4. Willingness-to-shift peak activities

To assess *willingness-to-shift* peak activities to other time periods, respondents were then asked, for each peak activity they selected in the previous question, "For your selected household activities, if the cost of electricity were to increase by 30% from 3pm to 9pm, would you or members of your household move this activity to another time period?" with response choices "Yes", "No" and "I don't know." This 30% price differential represented the midpoint of the range of price differentials under the TOU rates currently offered by their local utility. Response choices included "Yes", "No" and "Don't know". For respondents to report willingness-to-shift an activity outside of peak, they first had to report performing this activity in the peak period. To construct a willingness-to-shift measure, we therefore took the sum of all activities participants were willing to shift out of peak period and divided it by the total number of activities reported in the peak period, generating a willingness-to-shift metric between 0 and 1 (mean = 0.378; SD = 0.302). For example, if a respondent reported that they were willing to shift three out of the seven activities they reported performing in the peak period, their willingness-to-shift value would be 0.429. For a complete description of question wording, survey flow logic, and response distributions for peak activities and willingness-to-shift questions, reference S1 and S2 in the Supplemental Materials.

3.2.5. Demographic and home characteristics; household energy usage

Additional variables of interest applied in our analysis included demographics and home characteristics (see Table 1 for question content and summary statistics). Demographic measures included age, gender,

[1] A total of 391 responses were received through the Qualtrics panel, but only 329 were deemed "good completes," meaning that the respondent had completed the entire instrument and their time to complete was not less than 3 min and 40 s (one-third of the median completion time from the initial soft launch). Attention checks were also included at multiple points during the survey to ensure quality responses; responses were removed for any respondents that failed an attention check. An additional eight responses were collected by recruiting Fremont-area residents through city-wide newsletters and at local sustainability-focused events.

[2] Response categories were not randomized. We do not find evidence of order effects, with the most commonly reported response items appearing near the beginning and end of the category list.

[3] Respondents were only asked about this activity if they reported they owned an electric vehicle in a previous question.

race/ethnicity, income, and education. In terms of home characteristics, respondents were asked to indicate the number of household members (adults, children, and seniors) who lived in their household; whether the respondent owned their home; their home's square footage; and the deployment of smart technologies. We also asked participants to estimate their recent monthly electricity bill in U.S. dollars.

3.3. Analysis

To uncover patterns in participant data, we first summarized responses to energy rules (RQ1), activities performed in the peak period (RQ3), and willingness-to-shift these activities (RQ4) using descriptive statistics (see Table 2 for more detail). We then used ordinary least squares regression to fit three sets of model specifications. In the first set of model specifications, we explored how the level of energy rules participation is shaped by demographics and home characteristics, estimated electricity bill, and motivations for following household energy rules (RQ2). In the next set of model specifications, we considered how a respondent's willingness-to-shift certain activities outside the peak window is associated with demographics, home characteristics, energy rules, estimated electricity bill, and number of peak activities[4] (RQ5). In the third and final set of model specifications, we considered how these aforementioned measures contribute to the respondent's estimate of their electricity bill, a measure we included as an independent variable in previous specifications and now model as a dependent variable with demographics, home characteristics, energy rules, reported peak activities, and willingness-to-shift (RQ6). Missing data was deleted listwise, with all models utilizing at least 87% of the total sample (or 293 out of 337 data records). See Table 2 for a summary of dependent and independent variables applied in OLS model specifications.

Table 1
Variable measures and descriptive statistics.

Variable	Question(s)/Categories	Descriptive Statistics
Age	In which year were you born? (Converted to age in years)	M = 47.3; SD = 15.9 46.4% of respondents reported age over 50 years old
Gender	0 = Male 1 = Female	52.5% Female
Race/ethnicity	0 = All else 1 = White only	35.0% White only
Income	Including all income sources, which category best describes the total combined income of all members of your household for the last year, before taxes and deductions? 1 = Less than $10,000 A range of income levels was provided, up to: 12 = $300,000 or more	Median = between $100,000 and $149,000
Education	What is your level of formal education? 0 = Less than bachelor's degree 1 = Bachelor's degree or higher	65.9% reported having obtained a bachelor's degree or higher
Household size	For each of the following categories, how many people, including you, usually live in this home? (Total of children, adults, and seniors)	M = 3.01; SD = 1.76
Home ownership	Is your home … 1 = Owned by you or someone else who lives in the home 2 = Rented 3 = Occupied without payment of rent	73.0% owner-occupied
Home size	About how many square feet is your home?	M = 1625.5; SD = 791.5 48.8% of respondents reported more than 1500 square feet
Smart technology	Do you or any member of your household own or use any of the following? -Solar panels that generate electricity -Plug-in electric vehicle -Smart Thermostat (Nest, Ecobee, etc.) -Smart light bulbs (Philips Hue, etc.) -Smart appliances (Samsung Family Hub refrigerator, Bosch Home Connect dishwasher, etc.) -Home energy storage battery (Tesla powerwall, etc.) -Amazon Echo (Alexa) or Google Home	None = 47.5% 1 technology = 25.2% 2 technologies = 16.6% 3 technologies = 6.5% 4 technologies = 3.6% 5 technologies = 0.3% 6 technologies = 0.3%
Estimated electricity bill	Without looking at your electric bill, what is your best estimate of this month's electric bill? (in $)	M = $119.43; SD = 93.284

4. Results

4.1. What household energy rules govern energy use? (RQ1)

Of the 16 rules that respondents were provided (Fig. 1), respondents were consistent in their acknowledgement of what they considered to be household rules ("Not a rule" vs. a household rule), and on average

Table 2
Research questions, methods, and variables applied in analyses.

Research Question	Analytic method	Variable(s) applied
RQ1: What household energy conservation rules do respondents report govern energy use?	Descriptive statistics	*energy rules participation, energy rules index*
RQ2: What factors shape participation in household energy conservation rules?	OLS regression	<u>Dependent variable</u>: *energy rules index* <u>Independent variables</u>: *demographics and home characteristics, estimated electricity bill, rules motivations index*
RQ3: What energy-using activities do respondents report performing in the peak period?	Descriptive statistics	*peak activities*
RQ4: What energy-using activities do respondents report being willing to shift out of the peak period?	Descriptive statistics	*peak activities, willingness-to-shift peak activities*
RQ5: What factors shape willingness-to-shift peak activities?	OLS regression	<u>Dependent variable</u>: *willingness-to-shift peak activities* <u>Independent variables</u>: *demographics and home characteristics, estimated electricity bill, energy rules index*
RQ6: What factors, including use of smart technology, are related to a household's total energy use?	OLS regression	<u>Dependent variable</u>: *estimated electricity bill* <u>Independent variables</u>: *demographics and home characteristics, energy rules index, peak activities, willingness-to-shift peak activities*

[4] See Supplement Materials S3 for OLS regression models with peak activities as the dependent variable and demographics, home characteristics, energy rules index, estimated electricity bill, and willingness-to-shift as independent variables.

reported following 14 of the 16 rules. Perhaps most notably, one-third of respondents reported that they followed *all* 16 rules within their households to some extent. The most common household rules were “Wait to wash laundry until you have a full load” (98% reported as a household rule) and “Turn off the lights when you are the last person to leave a room” (98% a household rule), while least common rules were “Turn off the oven 10 min early” (58% a household rule) and “Turn off power strips when not in use” (68% a household rule). However, while the acknowledgement of these household rules was prevalent among our respondents, there was variation in how frequently these household rules were followed.

The rule respondents followed with the highest degree of regularity was “Keep doors/windows closed when AC or heat is on” (71% reported doing this “All of the time”). Other rules that at least half of respondents reported following “All of the time” included the following: “Turn off TV when you are the last person to leave a room (63% “All of the time”), “Turn off air conditioning or heat when no one is home” (62% “All of the time”), and “Turn off the lights when you are the last person to leave a room (60% “All of the time”), and “Fill the dishwasher to capacity before washing” (56% “All of the time”). Rules least likely to be followed “All of the time” included “Turn off power strip when not in use” (16% “All of the time”), “Dry clothing on a clothes line, rack, or hangers instead of the dryer” (11% “All of the time”), “Take showers that last 5 minutes or less” (8% “All of the time”), and “Turn off the oven 10 minutes early” (5% “All of the time”).

4.2. *What factors shape participation in household energy rules? (RQ2)*

In our baseline model of the energy rules index (Table 3; Model 1A), age, race, and estimated electricity bill are all statistically significant, with respondents who are older ($\beta = 0.226$; $p < 0.01$), female ($\beta = 0.111$; $p < 0.05$) and who report lower electricity bill amounts ($\beta = -0.271$; $p < 0.001$) also reporting higher levels of rule participation, while those who are white (vs. nonwhite) ($\beta = -0.160$; $p < 0.05$) reporting lower levels (Model 1A). In Models 2A and 3A, we consider four potential motivations for following energy rules (saving money, saving the environment, teaching members of the household, and avoiding wastefulness), all of which are statistically significant with more energy saving rule participation. Similarly, when these four motivational factors for following energy rules are formed into a single index, this index is statistically significant ($\beta = 0.368$; $p < 0.001$) and has the highest magnitude effect compared to other included measures on energy rules participation (Model 3A). Examining the fit (i.e., R-squared) of these models, Model 2A, which included motivations for following energy rules, explains approximately two times the variation in our energy rules index ($R^2 = 0.288$) compared to the baseline model (Model 1A; $R^2 = 0.133$).

Table 3
Ordinary least squares regression models for household energy rule participation. The dependent variable for Models 1A, 2A, and 3A is *energy rules index*.

Independent variables	Model 1A	Model 2A	Model 3A
	Coefficients	Coefficients	Coefficients
Demographics and home characteristics	Standardized	Standardized	Standardized
Age	0.226**	0.169**	0.171**
Female (vs. male)	0.111*	0.050	0.053
White (vs. nonwhite)	−0.160*	−0.099	−0.100
Bachelor’s degree or higher	−0.047	−0.005	0.000
Household income	0.079	0.009	0.009
Number of household members	0.055	0.024	0.017
Homeowner (vs. non-homeowner)	−0.005	0.009	0.011
Home square footage	−0.031	0.018	0.020
Estimated electricity bill	−0.271***	−0.281***	−0.279***
Smart technology	0.094	0.057	0.054
Motivations for following energy rules			
a. Saving money		0.119*	
b. Saving the environment		0.131*	
c. Teaching members of household		0.135*	
d. Avoiding wastefulness		0.145*	
Rules motivations index (a-d)			0.368***
Constant (unstandardized)	3.329***	2.297***	2.359***
R-squared	0.133	0.288	0.286
N	299	293	293

Significance level denoted with asterisks: *p < 0.05; **p < 0.01; ***p < 0.001.

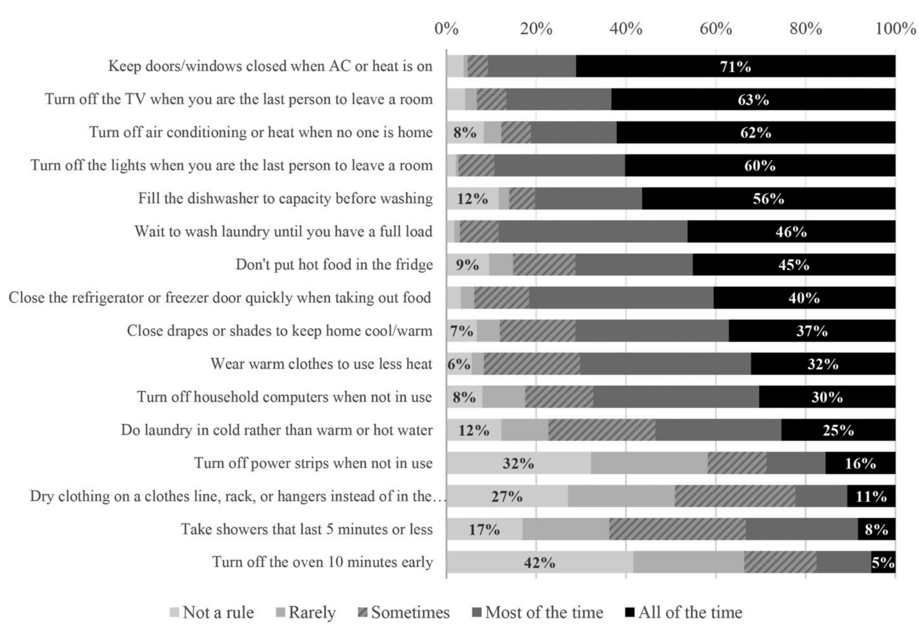

Fig. 1. Participation in household energy rules. Bar represents the reported frequency at which respondents report following energy rules. Response categories include “Not a rule”, “Rarely”, “Sometimes”, “Most of the time”, and “All of the time”.

4.3. What energy-using activities occur in the peak period (RQ3) and which are respondents willing to shift? (RQ4)

Of the 12 peak activities offered to respondents, watching TV (90%), cooking with oven/stovetop (88%), using a computer/tablet/game console (84%), and using lights (84%) were the most commonly reported, with at least 5 out of 6 households reporting performing each activity regularly (Fig. 2). Electric cooling (72%) was the next most commonly reported activity. In contrast, heating (45%) was reported less frequently, which could be due to the survey being conducted in the summer months. Showering (52%) was four times more common than taking a bath (13%), with approximately half of respondents showering. Cleaning activities, such as using the washing machine (48%), clothes dryer (46%), and dishwasher (40%), were also reported less frequently. Lastly, charging an electric vehicle (4%) was the least common activity reported by respondents. This option was only available to respondents who had previously indicated that their household had an electric vehicle, which was approximately 11% of the sample, and suggests that roughly one-third of respondents who owned an electric vehicle reported charging it during the peak demand window.

In terms of willingness-to-shift peak activities, we found that the most commonly occurring activities were also those respondents reported being least willing to shift. Fewer than one-quarter of respondents who reported watching television (22%) or cooking (22%) in the peak demand window indicated a willingness-to-shift those activities. Respondents who reported using lights (27%), computers (29%), electric cooling (25%), and electric heating (29%) also had low levels of willingness-to-shift these activities. In contrast, cleaning activities appear the most flexible. At least 80% of respondents who reported performing each cleaning activity in the peak demand window were also willing to shift it (washing machine: 80%; clothes dryer: 80%; dishwasher: 84%). Bathing activities were also somewhat flexible, with most respondents reporting performing these activities also willing to shift them (showers: 52%; baths: 53%).

4.4. What factors shape willingness-to-shift peak activities? (RQ5)

Our baseline model of willingness-to-shift peak activities reveals a relationship with home square footage, number of household members, and deployment of smart technologies, with higher square footage (larger homes) associated with a lower likelihood to shift peak activities ($\beta = -0.220$; $p < 0.01$), while more household members ($\beta = 0.122$; $p < 0.05$) and more deployed smart technologies ($\beta = 0.141$; $p < 0.05$) are associated with greater willingness-to-shift peak activities (Table 4; Model 1B). Introducing our energy rules index (Model 2B), greater participation in household energy rules is associated with higher willingness-to-shift peak activities ($\beta = 0.137$, $p < 0.05$). Additionally, a higher number of reported peak activities ($\beta = 0.128$, $p < 0.05$) (Model 3B) is associated with an increased willingness-to-shift. Compared to the previous set of energy rule participation models (Table 4; Model 1B–3B), these willingness-to-shift models have lower overall fit (R^2 = 0.080–0.111).

4.5. Modeling reported household energy use (RQ6)

While in previous models we treated the electricity bill estimate as an independent variable, we now model it as a dependent variable to gain insight into how energy rules, peak activities, and willingness-to-shift peak activities relate to overall household electricity usage. Across all models (Table 5; Models 1C–4C) we find that education, number of household members, and household income are statistically significant,

Table 4
Ordinary least squares regression models for willingness-to-shift peak activities outside TOU. The dependent variable for Models 1B, 2B, and 3B is *willingness-to-shift*.

Independent variables	Model 1B	Model 2B	Model 3B
	Coefficients	Coefficients	Coefficients
Demographics and home characteristics	Standardized	Standardized	Standardized
Age	0.060	0.029	0.030
Female (vs. male)	−0.024	−0.039	−0.045
White (vs. nonwhite)	−0.060	−0.038	−0.058
Bachelor's degree or higher	−0.035	−0.028	−0.023
Household income	0.005	−0.006	−0.014
Number of household members	0.122*	0.115	0.107
Homeowner (vs. non-homeowner)	0.012	0.013	0.019
Home square footage	−0.220**	−0.216**	−0.203**
Estimated electricity bill	0.045	0.082	0.053
Smart technology	0.141*	0.128*	0.113
Behaviors in home context			
Energy rules index		0.137*	0.132*
Peak activities			0.128*
Constant (unstandardized)	0.363***	0.141	0.057
R-squared	0.080	0.096	0.111
N	299	299	299

Significance level denoted with asterisks: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

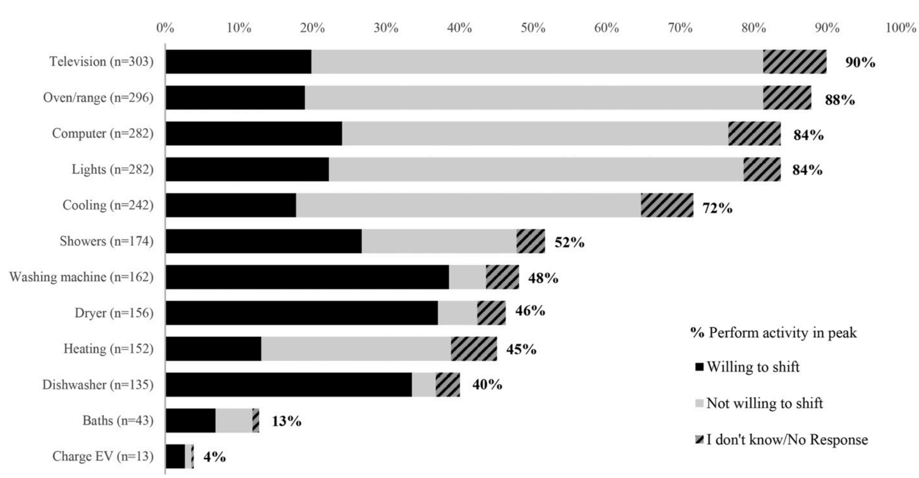

Fig. 2. Activity frequencies in peak and willingness-to-shift given 30% price increase. Overall bar represents the proportion of respondents who reported performing the activity in peak (e.g., 90% reported watching television in peak). Darker shading represents the relative proportion of respondents reporting this activity who were also willing to shift it out of peak given a 30% price increase.

with those with a bachelor's degree or higher reporting a lower estimated bill ($\beta = -0.245$; $p < 0.001$), while those with higher income ($\beta = 0.153$; $p < 0.05$) and more household members ($\beta = 0.207$; $p < 0.001$) reporting larger monthly bill estimates. Additionally, when we include our measure of energy rules and number of peak activities, we note that households that report greater rule participation ($\beta = -0.243$; $p < 0.001$) also report lower electricity bills, while those that report more peak activities ($\beta = 0.190$; $p < 0.001$) also report higher bills (Model 3C). We do not find a relationship between electricity bill and willingness-to-shift peak activities, although we do find in one of our models (Model 4C) that larger homes (square footage) are associated with higher electricity bills ($\beta = 0.117$; $p < 0.05$). Model fit improves substantially with inclusion of energy rules and activities in TOU (Model 3C: $R^2 = 0.244$) compared to the baseline model (Model 1C: $R^2 = 0.154$), suggesting the relative importance of energy behaviors in explaining electricity bill estimates.

5. Conclusions and policy implications

5.1. Household energy rules

In terms of household energy rules, we found that, for our sample, rules involving thermal comfort practices (i.e., keeping doors/windows closed when heating or cooling, turning off heating or cooling when no one is home) and electricity usage in unoccupied rooms (i.e., turning off TV and lighting when last person leaving a room) had among the highest levels of rule participation. We also observed variation within categories. For example, in the category of cleaning, running full loads in the dishwasher and washing machine had higher levels of reported rule participation compared to doing laundry in cold water and hang drying clothes. Rules related to cooking (i.e., don't put hot food in fridge, closing fridge doors quickly, turning off the oven early) had comparatively lower levels of participation in our sample, indicating rules intended to save energy use around cooking activities may be less prevalent than those related to comfort and cleanliness.

When we considered the factors that contribute to energy rules participation, we found that demographic measures of respondent age and race/ethnicity were important, as well as the respondent's estimated electricity bill. Additionally, when we considered motivations for following energy rules, *all* included measures were significant (saving money, saving environment, avoiding wastefulness, teaching family members), and when combined into an index, these collective motivations provide the most comparative explanatory power in our model. Such findings suggest that messaging strategies around TOU pricing implementation could prove salient for motivating residential customers above and beyond saving money. However, due to data availability, we were only able to test a narrow set of motivations, and we acknowledge that we have not captured all the potential reasons for why households may follow rules. Other important factors for shaping energy rule participation could include perceptions of family and social norms or the existence of habits (Maréchal, 2010).

5.2. Peak energy activities and willingness-to-shift

Our sample's reported peak activities largely aligned with peak activities reported in the more qualitative, smaller-N research that have typified activity-based analysis of potential responses to TOU pricing schemes thus far (Higginson et al., 2015; Ozaki, 2018; Öhrlund et al., 2019; Powells et al., 2014; Smale et al., 2017). High percentages of respondents in this sample reported performing entertainment and cooking activities during peak demand periods (e.g., watching television, using a computer, and cooking with stovetop/oven), yet these activities were also among the least likely for respondents to report being willing to shift. Our findings thus echo results from interviews with UK consumers by Powells et al. (2014), who found similar types of activities were regularly performed from 4pm to 8pm and that interviewees indicated a low ability to shift them.

Also, like Powells et al. (2014), who rated laundry activities as having a "medium" likelihood of performance in the peak period, just under half of our respondents reported doing laundry during the peak window. The broader implication is that certain activities appear to be more routinized than others. Both Powells et al. (2014) and Shove and Cass (2018) identified common schedules from work and school as responsible for routinizing behaviors such as cooking. In contrast, cleaning activities are often thought to be more "improvisational" and may be less likely to fall within natural daily schedules (Powells et al., 2014). The lack of temporal tethering for these activities allows for more flexibility, as reflected in the responses of our participants, who indicated the highest willingness-to-shift their use of washing machines, clothes dryers, and dishwashers. This finding aligns with previous

Table 5
Ordinary least squares regression models for electricity bill estimates. The dependent variable for Models 1C, 2C, 3C, and 4C is *estimated electricity bill*.

Independent variables	Model 1C	Model 2C	Model 3C	Model 4C
	Standardized Coefficient	Standardized Coefficient	Standardized Coefficient	Standardized Coefficient
Demographics and home characteristics	Standardized	Standardized	Standardized	Standardized
Age	−0.120	−0.056	−0.052	−0.053
Female (vs. male)	0.065	0.088	0.076	0.078
White (vs. nonwhite)	0.057	0.014	−0.016	−0.014
Bachelor's degree or higher	−0.245***	−0.240***	−0.222***	−0.221***
Household income	0.153*	0.162**	0.144*	0.144*
Number of household members	0.207***	0.207***	0.187**	0.181**
Homeowner (vs. non-homeowner)	0.096	0.088	0.093	0.092
Home square footage	0.109	0.094	0.108	0.117*
Smart technology	−0.034	−0.008	−0.031	−0.036
Behaviors in home context				
Energy rules index		−0.247***	−0.243***	−0.248***
Peak activities			0.190***	0.184**
Willingness-to-shift peak activities				0.045
Constant (unstandardized)	60.464***	167.193***	125.892***	124.871***
R-squared	0.154	0.210	0.244	0.246
N	299	299	299	299

Significance level denoted with asterisks: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

empirical analysis uncovered through interviews by Friis and Haunstrup Christensen (2016) and Smale et al. (2017), who found similar flexibility in cleaning practices.

5.3. Factors shaping willingness-to-shift

In assessing the factors that shape participants' willingness-to-shift activities outside of the peak window, we found three related to home characteristics: more smart technologies deployed in the home, greater numbers of household members, and less home square footage are all associated with increased willingness-to-shift. The relationship between smart technologies and willingness-to-shift may indicate that the mere presence of these technologies in the home makes the prospect of shifting easier and/or describes households that are more willing to engage in energy conservation behaviors.

In addition to smart technologies, these home characteristics—combined with our finding that households with more reported peak activities are also more likely to be willing to shift them—suggest potential complementary mechanisms for willingness-to-shift. On the one hand, households with more family members and more peak energy-using activities could have more opportunities for shifting, *especially* if such activities require coordination to meet needs specific to larger households with higher volume and frequency of activities (such as coordinating cooking, laundry/cleaning, etc.). However, the opposite could also be true, with certain households with fewer members and peak activities having potentially more opportunity for shifting, if such activities can be easily incorporated into a different routine. In this regard, our survey instrument, unfortunately, does not help us tease out these differences, as willingness-to-shift is represented as a proportion of activities reported. Testing if activities are coordinated across household members is even more challenging as we did not distinguish between willingness-to-shift for the respondent and the respondent's other household members. In this respect, our finding that homes that are smaller in size (e.g., less square footage) are associated with more willingness-to-shift could be capturing some of the mechanisms described above. One potential explanation is that space-constrained environments require more coordination of activities and this already existing coordination makes the prospect of shifting activities easier.

Somewhat surprisingly given the emphasis on household composition in the social practice literature, andthe focus on children in particular, when we ran models that included households with children (family members younger than 18 years old) and pets (cats and dogs) we did not observe significant effects. This could be due to how we chose to measure "children," which included both young children and older children who may behave more like adults within family dynamics and as energy consumers (Kavousian et al., 2013). Additionally, our households contained different mixes of children and adults which may make it challenging to tease out effects associated with families with children given the relatively limited size of our sample.

We also find evidence that energy rule participation is positively associated with increased willingness-to-shift activities. One potential interpretation to the relationship between energy rule participation and willingness-to-shift is that households that are more rule bound are better equipped to make temporal changes in energy activities, which may be achieved, for example, through a new set of rules around device/appliance use.

5.4. Household energy use

Our last set of findings considers factors that contribute to estimated electricity bill. These set of models are largely consistent with the existing literature on household energy use, with larger homes and higher incomes associated with higher bills, and higher education (bachelor's degree or higher) associated with lower bills. We also gain new insight into both our measures of energy rules participation and peak activities. Homes with higher numbers of reported peak activities have larger reported electricity bills, while homes with greater energy rules participation have lower estimated bills.

5.5. Policy implications

Our analysis identified some potential pathways of success for TOU implementation, as the high reported flexibility of cleaning activities could result in reduced peak demand for utilities. Yet, fewer than half of respondents reported performing these activities in the peak window, and those who did may be unlikely to perform them every weekday. In addition, although cleaning activities appear to be the most convenient to move, Strengers (2019) argued that this is not always the case for households, as activities like running the dishwasher depend more on household member availability than price. Meanwhile, energy-intensive activities, such as cooking and home temperature control through cooling or heating, were far more inflexible but also likely to occur more frequently. The implication for utilities, at least for our sample, is that TOU rates may have a limited effect on peak demand. This response may simply be due to a low-price differential between peak and off-peak, which has been cited as a problem in previous TOU pilots (Brown, 2003). There is also the possibility that there are simply inherent limitations on what households can change. Strengers (2019) noted that for families the evening peak period involves squeezing many practices into a short time period and results in fixed routines that are difficult to change, undercutting the goal of TOU prices. Utility companies and policymakers looking to variable TOU pricing as a solution to peak demand should likely temper their expectations about household demand responsiveness to such programs and possibly consider alternative pathways for motivating energy conservation.

Our analysis also identified several insights for influencing energy-using behaviors both within, and outside, the TOU peak rate period. First, we found that energy savings rules were related to energy conservation in two important ways: (1) energy rules participation was associated with willingness-to-shift energy-using activities outside of the peak period and (2) energy rules participation was associated with lower overall electricity use. Additionally, we found that energy rules participation was related to multiple motivational factors, including environmental, monetary, and educational reasons. Such findings suggest a role for utilities, policymakers, and advocates in promoting the importance of "household energy rules"—such a strategy could move educational efforts beyond the traditional approach of providing energy-saving tips by appliance. In contrast, this strategy would magnify the importance of existing household rules and renew efforts to adhere to those rules, as well as convey the importance of adding rules to stabilize household routines, while at the same time contributing to the success of demand response and TOU programs. While in our research we focused on 16 energy-saving rules, chosen for their generalizability across households, rules that target specific aspects of a family's lifestyle and are designed to provide the most energy savings, could be even more impactful for peak reductions. And while the focus of this research has been on conservation within the TOU peak period, many energy-savings rules apply to activities throughout the day, contributing to reductions in overall energy use.

Second, while not as prominent as other factors in our modeling, we did find evidence that adoption of smart technologies within the home was associated with a greater willingness-to-shift activities outside of TOU. While policymakers and scholars have debated the effects that increased home automation will have on energy conservation (Strengers, 2013), our findings suggest that having these technologies in the home did not reduce a respondent's reported willingness-to-shift peak activities. Whether policies that promote increased adoption of smart technologies will translate to substantive reductions in peak energy demand, however, remains an open question.

As TOU rates begin to become the default in California and potentially other locations, evaluation of their success would benefit from incorporating this practice-based perspective. The dilemma of how to reduce peak electricity demand will continue to be the focus of intense research. Our analysis is intended as a step in the direction of a larger sample, practice-based understanding of residential energy usage in the peak demand window.

5.6. Limitations and future research

Our overall findings are limited in terms of generalizability, given our nonprobability convenience sample. Additionally, the questionnaire only provided respondents with 16 possible energy conservation rules and 12 possible energy-using activities with no outlet for reporting additional energy rules or uses, meaning that many rules or activities were potentially uncaptured. There is also the possibility of measurement error due to people having limited or incorrect knowledge of their own energy behavior, as well as the potential for unintended survey architecture effects due to questionnaire design and non-randomization of response choices. For example, we first asked respondents to report their activities in peak and then asked about their willingness-to-shift these activities, meaning respondents were exposed to different, personalized lists of “shiftable” activities. Additionally, the questionnaire asked about activities that were *regularly* performed in the peak window, which is open to respondent interpretation and possibly recency bias, such as the summer timing of our survey influencing responses about cooling compared to heating. Furthermore, the use of a binary “yes” or “no” for peak activity reporting does not reflect any perceived levels of variation in the regularity of these activities being performed in peak (e.g., four days a week vs. every day). Relatedly, in terms of flexibility, respondents were given a binary choice of whether they would shift an activity, when the reality is that some activities are more likely to be shifted at certain times but not others, meaning the “flexibility of flexibility” is uncaptured. These issues, along with our survey design only allowing participants to shift activities that were first reported in peak (introducing a potential “floor effect” for households with few peak activities, though we explore and find little evidence for this effect in Supplement S2), suggest that our work may not account for some of the more nuanced aspects of demand response flexibility.

Future research that combines an understanding of household energy rules and practices with actual meter data would provide a more complete view of how routines aggregate into overall demand spikes. As TOU rate policies increasingly go into effect, research should focus on the transition of customers to TOU prices and evaluate practice flexibility in response to actual price changes as opposed to either the hypothetical approach taken by this analysis or the experimental approach of previous pilot studies. Future studies could also incorporate larger price swings and/or other types of motivations for shifting beyond cost, such as environmentally-focused messaging (Asensio and Delmas, 2015). TOU rates are likely to be tools of experimental market re-design (Powells et al., 2014) and deserve to be studied from multiple perspectives to create a more complete picture of their potential to create change.

Data availability

Data used in this study will be made available upon request from corresponding author.

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.

CRediT authorship contribution statement

Greg Stelmach: Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Chad Zanocco:** Methodology, Formal analysis, Writing - review & editing, Visualization. **June Flora:** Conceptualization, Methodology, Writing - review & editing, Project administration. **Ram Rajagopal:** Conceptualization, Supervision, Funding acquisition. **Hilary S. Boudet:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2020.111608.

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