Heterogeneity in time and energy use of watching television

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HIGHLIGHTS

- Utility and other efficiency programs often treat consumers as homogenous groups.
- Heterogeneity in consumer behavior affects benefits/costs of efficiency upgrade.
- Significant heterogeneity is found in U.S. television watching patterns.
- Heavy watchers (7.7 h/day) are 14% of population but consume 34% of energy.
- Energy savings of efficient television for heavy watcher is 3 times the average.

ARTICLE INFO

ABSTRACT

There is substantial variability in residential energy use, partly driven by heterogeneous behavioral patterns. Time-use is relevant to energy when consumption tracks the time a device is used. Cluster analysis is a promising approach to identify time-use patterns. If clusters with particularly long time use and thus high energy consumption emerge, these groups could merit targeted policy intervention. We investigate these ideas via an empirical study of time use for television watching in the U.S. Three clusters were identified. In 2013, the average time spent watching television by Clusters 1, 2 and 3 are dramatically different: 1.1, 3.5 and 7.7 h per day respectively. While members of Cluster 3 are only 14% of the total population they represent 34% of TV energy consumption. The population of Cluster 3 tends to be older, less employed and less educated. Energy savings per adopter is much larger for Cluster 3, suggesting much higher benefits from efficient devices. These results are relevant to the design of efficiency programs, indicating potential for variable rebates and/or tiered communication. With *variable rebates*, utilities would offer higher incentives to high-use customers. In *tiered communication,* utilities would devote more resources to engage customers with larger savings potential.

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1. Introduction

Promoting reductions in households is an important strategy to improve the environmental and economic performance of the energy sector. A variety of interventions are ongoing to improve energy efficiency, including standards, certifications, education, tax incentives and rebates. Utilities, local, state and federal government bodies are increasingly involved in promoting efficiency, including efforts in the commercial, residential and industrial sectors. Focusing on the U.S., utilities have more than three decades of experience running efficiency programs. Residential programs, mainly funded through approved rate increases (systems benefit charge), had expenditures of $1.7 billion in 2014, with most spent on financial incentives (54%), followed by administration

and marketing at (18%), R&D at 3% and other programs (25%) (CEE, 2015). Efficiency program expenditures are expected to double in the next decade (Barbose, 2014). The U.S. federal government also spent $300 million for supporting state level energy efficient appliance rebate programs (SEEARP) between 2009 and 2012. Similarly, many other countries such as China, South Korea, India, Denmark, Netherlands, France, Italy, UK, Japan and Mexico have federal energy efficiency programs (Can and de la, 2011; de la Rue du Can et al., 2014).

While there are many efforts to measure the cost-effectiveness of utility efficiency programs (National Action Plan for Energy Efficiency, 2008), it is difficult to conclusively estimate their contribution (Arimura et al., 2011). Whatever the current cost-effectiveness is, it is clearly desirable to improve it. One potential avenue to improve cost-effectiveness is to better account for consumer heterogeneity. Consumer heterogeneity includes differences between usage patterns of energy using devices (e.g. thermostat settings and schedule) and the technical characteristics of

those devices (e.g. efficiency of air conditioner). These differences are large, e.g. living room temperature of New York households in the summer ranged from 59 F to 75 F (Roberts and Lay, 2013) . The energy savings from an efficient air conditioner will be radically different for a household with a thermostat setting of 59 F compared to 75 F. Peak savings will also vary widely by consumer depending on thermostat schedule.

There is thus potential to improve the cost-effectiveness of utility efficiency programs by accounting for consumer heterogeneity. However, current utility practices generally treat consumers as a single average consumer, masking any differences in behavior or preferences. The typical course of action is for utilities to provide blanket information (e.g. website, flyer with bill) to all customers, then estimate benefits and costs based on average savings per replacement. With such an average customer approach, energy efficiency program expenditures between 1992 and 2006 conserved electricity at an average cost to utilities of 5.0 cents per kWh at 5% discount rates, with a 90% confidence interval that goes from 0.3 cents to nearly 10 cents per kWh saved (Allcott and Greenstone, 2012; Arimura et al., 2011). The average cost is significantly lesser than the national average retail price of 8.90 cents per kWh in 2006 (EIA, 2015), however the average cost does not include costs incurred by consumers. If the additional cost to consumers is 70% or greater of program costs, based on (Joskow and Marron, 1992; Nadel and Geller, 1996), energy efficiency programs become non-profitable at 10.4 cents per kWh (Allcott and Greenstone, 2012).

Heterogeneity implies that an efficiency measure, while cost-effective for the average, may not be cost-effective for some sub-groups, but may be particularly beneficial to others. If there is significant heterogeneity, treating consumers as homogenous and using an average consumer will skew the estimates for cost-effectiveness of the program. By accounting for heterogeneity, one can lower marketing cost and/or increase participation to improve the cost-effectiveness of household efficiency programs. For the air-conditioner example above, targeting the population with higher thermostat settings could save more energy with similar program costs.

Heterogeneity is typically addressed through market segmentation approaches i.e., identifying homogenous sub-population within larger heterogeneous population (Moss et al., 2008). One approach to segmentation is to group consumers according to common demographics, e.g. household size, income (Cayla and Maïzi, 2015). If the objective is to address energy use, one should group consumers according to the pattern of energy use, which may vary significantly within a specific demographic group.

The biggest challenge in addressing consumer heterogeneity is lack of data on how consumers are using different devices. In principle, different combinations of smart meters, smart power strips, load monitoring software and/or smart appliances commonly called as energy disaggregation technologies can address this problem (Carrie Armel et al., 2013). However, there are many challenges for adoption of these technologies in terms of (1) hardware cost, (2) the need for better load monitoring software and (3) privacy and security concerns. While the rate of smart meter adoption is growing, it will take some years before market saturation (Faruqui et al., 2011; FERC, 2014; IEI, 2014). In addition to smart meters, requirements of hardware, software and calibration are not clear to give time and device-resolved results. It is important to know the importance of heterogeneity to justify further development and investment in disaggregated energy monitoring technologies.

Time-use data presents an opportunity to understand consumer heterogeneity in energy use without an advanced energy monitoring system. Time-use data is the temporal sequence of activities that a person completes in a day, e.g. wake up at 6 AM,

make breakfast until 6:30 AM, and so on for an entire day, and potentially for multiple days. Time-use for an activity that involves particular devices (e.g. television and kitchen appliances) can be mapped to the energy use of the device. Note that the relationship between time use and energy use can be more complicated depending on the device. In the US, Bureau of Labor statistics conduct the American Time Use Survey (ATUS) each year.

We aim to segment consumers based on patterns in the time-use of energy consuming devices. We explore this idea to characterize television watching in the US. Televisions contribute significantly to the residential electricity demand in the U.S., consuming 7% of national purchased electricity (EIA, 2015). For comparison, note that shares for other appliances are: space heating (8.4%), space cooling (13.2%), water heating (9.2%) and refrigeration (7.5%). Furthermore, television energy use is likely increasing since people spend more time using televisions and consumer electronics each year (BLS, 2015a; Nielsen, 2015) and the average screen size has increased by 17% between 2010 and 2013 (Urban et al., 2014). Results from this analysis will identify sub-groups with differing television energy use, which in turn informs utility rebate programs to encourage consumers to switch to efficient televisions. The analysis of television use, a useful case study in its own right, also serves as a vehicle to explore a general approach to characterizing heterogeneity in energy use.

2. Methodology and data

2.1. American Time Use Survey (ATUS) dataset

The American Time Use Survey (ATUS) is a yearly survey conducted by the Bureau of Labor Statistics (BLS) since 2003. Annual participation in the survey exceeds 11,000 respondents. Only one household member is sampled per household. The survey is conducted using computer-assisted telephone interviewing in which the respondents respond on how they spent their time on the previous day, where they were, and whom they were with. Conducting the survey via a conversational interviewing style mediated by an expert is thought to improve reporting accuracy.

ATUS defines television watching as any of the following: (1) using a television to watch video programs and movies via broadcast, cable, DVD, VCR, or the internet and (2) using a computer to watch video and (3) setting up DVD/VCR player, TiVo/DVR. In addition to the time-use information, ATUS also collects respondent's household level socio-economic data such as age, income, sex, race, marital status, education level and employment status. More information on the ATUS survey can be found on the ATUS website (BLS, 2015a).

2.2. Model

We develop a model that uses ATUS data to divide consumers into multiple segments based on their television-watching pattern. A consumer segment with similar television watching pattern is also referred as cluster. Division into consumer segments/clusters is followed by characterization of energy use and socio-economic characteristics. Energy use characteristics are used to inform the potential energy savings from each segment, while socio-economic characteristics allow us to target segments with highest savings potential.

The model consists of three main parts, data processing, pattern classification and an energy model. In the data processing stage, the sequence of start and stop times of television watching in ATUS is transformed to a box function with 0 as not watching and 1 as watching television for time bins. In the pattern classification stage, the respondents are grouped into clusters based on
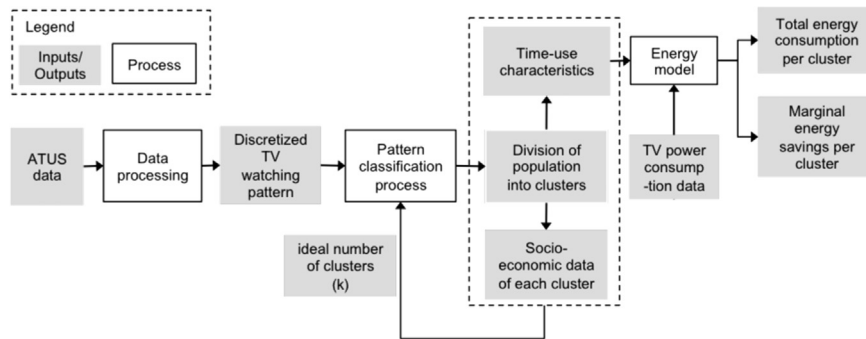
Fig. 1. Description of the model developed to characterize consumer heterogeneity in TV energy use.

similarities in their television watching patterns. In this stage, the cluster characteristics such as population, time-use and socio-economic characteristics are characterized through descriptive statistics. Finally, the energy model maps time-use to energy use estimates for each cluster. Fig. 1 illustrates the model developed and flow of data. A detailed description of the model follows.

2.3. Data processing

The data processing stage converts the ATUS dataset into a discretized representation of when people are watching and not watching television. This discretized representation is more mathematically tractable for pattern classification. For each respondent, ATUS activity data lists the sequence of activities performed with their start and stop times. The initial step in data processing is to rewrite the activities into "Watching TV" or "otherwise". Then a discretized television watching profile for each respondent is specified using the following function:

$$\delta(t) = \begin{cases} 1 & \text{if Watching TV in time interval } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where t denotes the time interval number after dividing a 24-h day into 256 equal intervals i.e., 5.625 min. The resultant pattern has a "box-like" geometry. Fig. 2 illustrates the data processing stage for one hypothetical respondent.

2.4. Pattern classification

In this stage the binary representation of respondents' television pattern are grouped into clusters depending on a measure describing similarities between the patterns. The goal is to develop a scalar "distance" measure of similarity between the television watching patterns, i.e. the distance is small for similar patterns and large for dissimilar patterns. In order to describe similarities,

features of the pattern should be extracted. Examples of features in a pattern are the number, time and width of peaks. There are many possible measures for feature extraction; we follow a commonly used approach known as the Walsh-Hadamard transform. The idea is to transform the binary representation, as shown in Fig. 2, into a Fourier-like frequency spectrum. The Euclidean distance between two frequency spectrums is the measure used to describe similarity of the television-watching patterns.

To explain in more detail, the binary representation of a daily television-watching pattern is a set of 256 values consisting of 0's and 1's. The choice of 256 time intervals came from the requirements of the Walsh-Hadamard transform to have input data of the order 2^n. The Walsh-Hadamard transform represents the binary sequences as a superposition of basis box functions (or Walsh function). The transformation yields a set of coefficients, a 256-element vector of real numbers, each coefficient reflects the strength of contribution of a Walsh function to the superposition, equivalent to a frequency spectrum from Fourier analysis. Note that like a Fourier transform, a set of Walsh-Hadamard coefficients can be mapped back to a time profile of an activity pattern. More information on Walsh-Hadamard transform can be found elsewhere (Beauchamp, 1984; Beer, 1981; Walsh, 1923). Application of this methodology can be widely seen in travel behavior analysis, e.g. (Chen, 2013; Recker et al., 1985).

Following the Walsh-Hadamard transformation, segmentation or clustering is conducted using the k-means algorithm (MacQueen, 1967). The idea of k-means clustering is to pick k randomly selected respondents as initial centroids on which to build clusters. Each member of the population is assigned the cluster with smallest Euclidean distance from the centroid. Given these initial clusters, a new centroid is calculated as the average of each cluster population. The process of distributing the population into clusters is repeated until there is no further reassignment to clusters. A detailed description of k-means clustering can be found elsewhere
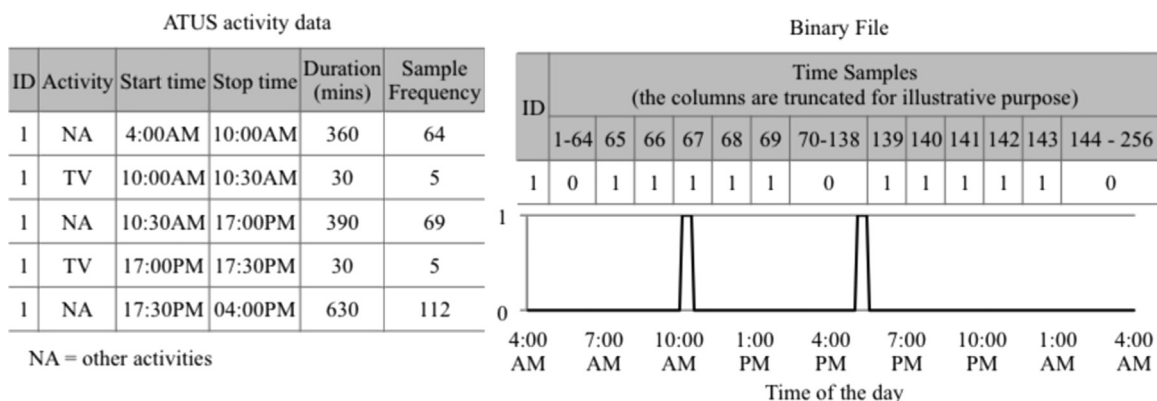

Fig. 2. Illustration of data processing stage for one hypothetical respondent: from ATUS sequence of start and stop times to box-like binary representation.

(Duda et al., 2000; Kogan, 2007). For the reader interested in more technical details, note that we used weighted k-means clustering where weighted averages and weighted Euclidean distance were calculated. This is because the ATUS survey comes with weights that map an individual's response to their representation in time-use of the overall U.S. population.

The result of the above process is division of the population into k-clusters. Next, the inverse Walsh–Hadamard transformation is used to obtain representative cluster or cluster average television patterns. The cluster average pattern can be interpreted as the probability of an average cluster member watching television at a particular time of day. An alternate interpretation is what fraction of the cluster is watching television at a particular time. Given cluster membership, cluster characteristics are estimated using descriptive statistics. The cluster characteristics measured includes population of the clusters, time-use characteristics such as total television viewing time and number of times television watched in a day, socio-economic characteristics such as age, gender, income, education, marital status, employment status and number of household members and etc. Survey weights are used to normalize the results to represent the U.S. population.

Given the number of clusters k, the above procedure describes how to divide the population into k clusters. However, it is not clear a priori what value k should take, i.e. how many clusters are ideal. Obviously higher k reduces distances of members from centroids i.e. clusters are more homogenous. However, the objective is to find the smallest value of k that succinctly describes heterogeneity. The following procedure summarizes the methodology to identify the ideal number of clusters k. For any given number of clusters, cost is defined as the summation of the weighted distance between all the respondents to their closest cluster center. To identify the ideal k value, a cost function is developed. The cost function provides the cost for a set of cluster numbers, $y=\{2,3,4...n < N\}$ where N is the number of observations in the dataset. The cost function always decreases monotonically. Therefore, a range of k-values are initially chosen based on when there is a turning point in the marginal reduction in cost from increasing k, i.e. the "knee point of the curve"(Theodoridis and Koutroumbas, 2008). For the range of k-values chosen, detailed cluster characteristics are found. The best k among these is chosen as the value for which every cluster is clearly distinguishable based on the cluster characteristics.

2.5. Energy model

The goal of the energy model is to measure total energy use of each cluster and the expected marginal energy savings when a member of a cluster upgrades to an efficient television. The baseline year for the energy model is 2013.

Total energy use of each cluster for television watching in the year 2013 is calculated using the formula shown in Eq. (2).

$$\text{Total Energy use}_k = p_k \times \left(t_k \times W_{active} + (24 - t_k) \times W_{standby} \right) \quad (2)$$

where k is the number of clusters identified; p_k is the population of each cluster; t_k is the total time spent watching television for each cluster; W_{active} is the power consumption of an average 2013 TV and $W_{standby}$ is the standby power. We neglect heterogeneity in television models and use average values for active and standby power consumption. Urban et al. (2014) reports the average active power consumption as 90 W and 1.6 W in standby mode for the year 2013. Note that differences between clusters in terms of television ownership (technology, vintage and screen size) are not covered in ATUS. While a possible topic for future work, here we isolate the effect of watching pattern heterogeneity on television energy use.

Eq. (3) gives Per person or marginal energy saving per cluster

$$\text{Marginal Energy Savings}_k = t_k \times (W_k - eW_k) \quad (3)$$

Where, eW_k is the active power consumption of the efficient TV. The efficient TV is assumed to be 40 in. LCD TV compliant with EnergySTAR V7.0, which became October 2015 (EPA, 2015). Note that ENERGY STAR compliant televisions accounted for 84% of the sales in 2013, 96% of these 32.9 million units were LCD televisions (EPA, 2014). Also, the average size of the television stock has been increasing, 29 in. in 2010 and 34 in. in 2013 (Urban et al., 2014). We draw on Energy star requirements to determine the power consumption of the efficient television eW_k. The efficient television is assumed to meet ENERGY STAR specification V7.0 with a 40-inch TV an aspect ratio of 16:9, resulting in maximum active power consumption of 37.6 W. We assume this is a reasonable measure of the average power consumption, thus $eW_k=37.6$ W.

2.6. Literature review

While there are a variety of works linking time and energy use (Torriti, 2014), none of these studies characterize time-use heterogeneity, and in turn, energy-use heterogeneity. To briefly summarize prior work, Schipper et al. (1989) discuss qualitative differences between breakdown of energy use and time use for different activities. The earliest time-use based energy model was developed by Capasso et al. (1994). They use a probabilistic approach to model activity pattern of each household. Since a time-use survey only provides information about a single person in a household, probability of an activity to be performed in a household is modeled based on demographic characteristics of individual member in the household. The synthesized activity data is mapped onto different end-use technologies to generate residential load curves. Recent extensions of Capasso et al. (1994) include the use of probabilistic and/or stochastic techniques to accurately synthesis activity data for households. Many researchers (Johnson et al., 2014; Muratori et al., 2013; Richardson et al., 2009, 2008; Widén et al., 2009; Wilke et al., 2013) use Markov chain approach to predict activity of an individual with particular demographic characteristic. Subbiah et al. (2013) classifies individual based on their demographic and uses a probabilistic model to predict activity of each class. Chiou et al. (2011) uses a bootstrap sampling method to derive activity profile of individual in a household.

Validation of these approaches have shown that mean time for any activity can be predicted with high degree of confidence however diurnal variations (peak energy use) are not accurately preserved. This shortcoming is attributed to the inability of the model to address heterogeneity in activity pattern of the household. Furthermore, mapping time-use survey defined activities to end-use technology can be problematic. For example, accurately mapping cooking activity to energy use requires further information on type of food cooked, the efficiency of the equipment used and number of minutes each equipment is on. Therefore, insufficient data and heterogeneity in the physical characteristics of equipment contribute to model inaccuracy.

The policy intent of the aforementioned models has been to inform decisions on demand response, energy efficiency and microgrid implementation programs. The application of these models included visualizing load curves for different attributes such as building type (attached vs detached), type of day (weekend vs weekdays and winter vs summer), occupancy, household type (family vs single, or working household vs non-working household). However, no definite or strong policy connections with respect to these attributes were made.

Some researchers use time-use surveys to focus on the activity specific implication on energy use or energy implications of a specific group of consumers (López-Rodríguez et al., 2013). Torriti

(2012) studied occupancy variance with time-of-day of single-person households in 15 European countries. According to him, during peak times (8–8:10 PM), most single family households were watching television. In Spain, television watching is the activity with highest simultaneous percentage of household involvement during peak hours (Santiago et al., 2014). Other time-use application includes quantifying the economic impact of harmonic losses from audio visual devices in the residential sector (Santiago et al., 2013).

To summarize, while these models provide new ways to link time-use with equipment-specific energy use, they did not do the following: (1) address heterogeneity in the end-use technology usage pattern, (2) link demographic with the heterogeneous usage pattern and (3) connect to policy with respect to consumer heterogeneity. We address these three points in this paper.

Addressing heterogeneity through market segmentation has a long history. In utility energy efficiency programs, market segmentation models have focused on segmenting customers by demographic variables. Sometimes researchers also segment based on lifestyle and/or attitude of the population (Moss et al., 2008; Stern et al., 1986). These approaches were used for marketing purposes only. However, by addressing heterogeneity, utilities can re-structure their planning and marketing strategies of the energy efficiency programs. To our knowledge this is the first work to segment population based on the time-use (and thus energy use) pattern, followed by socio-economic characterization of the segments.
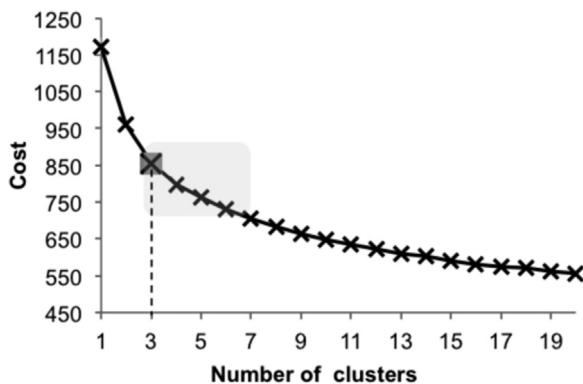
3. Results and discussion

The model described in Section 2 was built in MATLAB. The model outputs for input data corresponding to year 2013 are discussed in this section.

3.1. Cost function for different numbers of clusters

The cost function as function of cluster number k is shown in Fig. 3. As discussed in Section 2.4, the ideal number of clusters is at the knee of the curve, in this case between 3 and 6. In order to choose the best k value, the average time spent and watching pattern of the subgroups were compared for $k=\{3, 4, 5, 6\}$. For the best k value all sub-groups are distinguishable in time spent and watching pattern. $k=\{4, 5, 6\}$ were rejected because there were at least two very similar subgroups for each. See Fig. S1 in the Supporting information for results when $k=4$. The best value of k was thus chosen to be 3.

3.2. Heterogeneity in television watching pattern

The sample of respondents is divided into 3 clusters whose average television-watching patterns are shown in Fig. 4 along with the average pattern of the total population. The y-axis of the figure can be interpreted as either the watching pattern of an average person in the cluster or the percentage of population in the cluster watching television. In addition, the figure also summarizes cluster characteristics such as, population, average time spent watching television and average number of television watching activity (frequency). The clusters are sorted in ascending order based on average time spent watching television and named cluster 1, cluster 2 and cluster 3 respectively.

According to the American Time Use Survey, the percentage of people watching television increases gradually from 7 AM until 4 PM. The share of population then increases swiftly and reaches a peak at around 7:45 PM, where 40% of the population watches television. After the peak, share of population decreases progressively until 4 AM.

Heterogeneity in television time-use is significant. An average person in cluster 3 spends almost three times more time watching television than the average person in the total population, 2 h and 46 min. Further there are significant differences between the clusters regarding the television watching peak. Cluster 1 does not have a distinct peak compared to clusters 2 and 3. It is interesting to note that the peak of cluster 2 occurs approximately at 8 PM the same time as the peak of average watching pattern of total population. Again cluster 3 has a distinct watching pattern with multiple peaks at 3 PM and 6:45 PM.
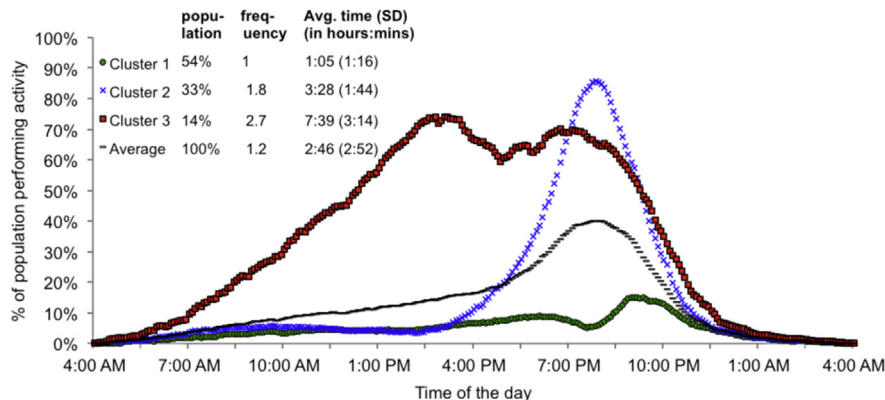

Fig. 3. Cost function developed for a set of clusters $y = \{1, 2...20\}$ for the year 2013 data. Ideal number clusters, $k=3$.


Fig. 4. Television watching pattern of U.S households in 2013, by cluster. Average refers to total population not divided into clusters. Frequency is the average number of television watching activities. SD=standard deviation.

Dividing the population based on time-use results in larger heterogeneity than demographic-based segmentation. For example, using the same ATUS data, television watching time varies between 2 and 4 h when segmenting based on different age groups (BLS, 2015b).

3.3. Cluster with maximum energy savings potential

Based on the average time and population characteristics, energy use of clusters 1–3 were calculated to be 23, 36 and 31 GW h/day
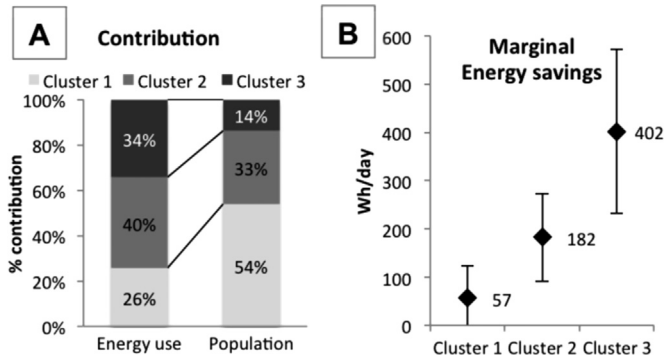
Fig. 5. Summary energy use statistics of the clusters. (A) Total energy use of televisions watched by respondent in each cluster. (B) Energy saving from replacing television in one household with efficient 2015 model. The range refers to the standard deviation of television watching time within cluster.

respectively. Fig. 5A shows the energy use and population of each cluster as a percentage of their total. The result shows that even though cluster 1 has the most population they contribute the least to the total energy while cluster 3 has the lowest population of 14% but contributes the second most 34% to the total energy. Heterogeneity in the total time spent watching television is the driving factor for differences in energy use. Time-use for other energy-consuming devices will presumably have different degrees of heterogeneity, those devices with large heterogeneity are obviously those most important for the cluster analysis developed here.

Fig. 5B shows the marginal energy savings when an individual's television (90 W_{active} and 1.6 $W_{standby}$) is replaced by an efficient television (37.6 W_{active} and 1.6 $W_{standby}$). The marginal energy savings potential from targeting one individual in cluster 3 is 7.1 times and 2.2 times greater than targeting an individual in clusters 1 and 2 respectively. Further the savings from clusters 2 and 3 could reduce peak demand (see Fig. 4). These results show that Cluster 3 is a suitable candidate for targeted policy interventions.

3.4. Socio-economic characteristics of the clusters

In order to understand membership in the clusters, we analyzed a number of socio-economic variables of the respondent and their household. Here we show results for only those variables with significant differences between the clusters. Other socio-economic characteristics can be found in the Supporting information.

Results for employment status of respondent, marital status or
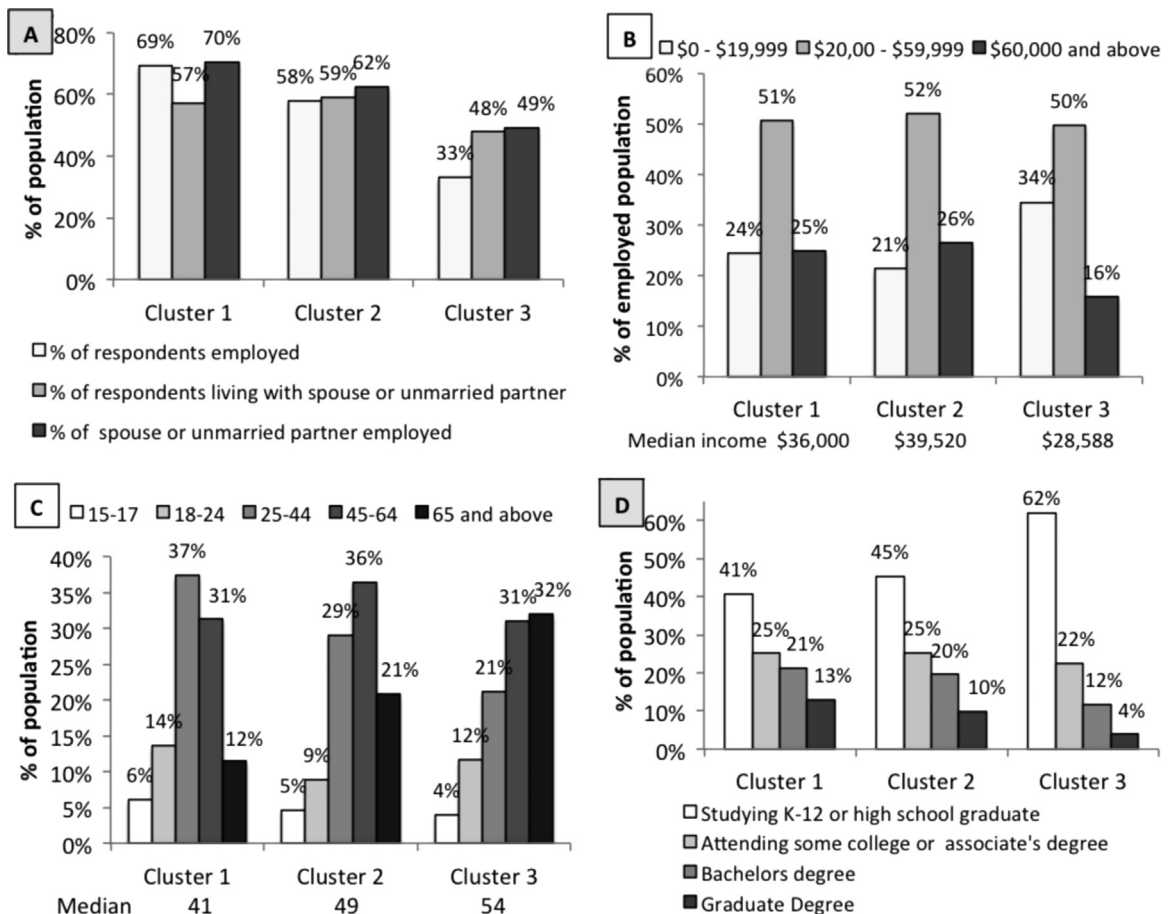
Fig. 6. Summarizes the socio-economic characteristics of the clusters. A - employment status of the respondent and their spouse or unmarried partner categorized by clusters. B - annual individual income distribution of the employed respondents categorized by clusters (in 2013 dollars). C - age distribution of the respondents categorized by clusters. D - education status of the respondents categorized by clusters.

unmarried partner, employment status of partner, income, age and education level of respondent are shown in Fig. 6. Compared to clusters 1 and 2, cluster 3 is significantly different with respect to a number of socio-economic factors. Cluster 3 consists of population who are older, less educated and largely unemployed or holding part-time employee status, relative to other clusters. The major differences between cluster 1 and 2 are the employment status of the cluster members and their partners and the number of younger children present in the household. Compared to cluster 2, cluster 1 has a higher share of employment for both the respondent and their partner. Cluster 1 households also have more children (less than 18 years old) compared to cluster 2. The average age of the youngest child in cluster 1 is also lower than cluster 2. For other socio-economic characteristics, the difference between Cluster 1 and 2 are minor. Fig. 6 contains four subfigures that summarize demographic differences.

Employment: Fig. 6A shows the employment status of respondent and their spouse or unmarried partner. Clusters 1 and 2 consists of at least 2 and 1.7 times more percentage of population employed when compared to cluster 3. In addition, more than 50% of those employed in cluster 3 are part time workers while clusters 1 and 2 consists of 20% and 25% respectively. Therefore, television time spent is inversely related to employment status. There is no significant variability between the clusters with respect to the percentage of population married or living with unmarried partner. However, the employment status of the partners follows similar trend as the employment status of the respondent. Cluster 3 consists of larger percentage of the partners unemployed or working part time. The employment of respondent and their spouse or unmarried partner may indicate less leisure time in the household therefore lesser time for watching television.

Income: Fig. 6B shows the annual income distribution of the employed population in each cluster. The results are summarized for only those individuals who reported being employed. Since cluster 3 has a relatively larger population unemployed or working part time lower income is expected for that cluster compared to clusters 1 and 2. The results indicate the same.

Age: Fig. 6C shows the distribution of age groups in each cluster. The median age of cluster 1, 2 and 3 are 41, 49 and 54 years. The age distribution is skewed to the left as we move from cluster 1 to 3.

Education: Fig. 6D shows the education status of each cluster. As employment status and income are correlated with educational level, the prior results on income and employment suggest that the education status of cluster 3 is lower than clusters 1 and 2. As expected, the results show the same, more than 60% of cluster 3 are either studying or high school graduate while only 40% fall in the same category for cluster 1 and 2. Also, clusters 1 and 2 have higher share of people with bachelors and graduate degree compared to cluster 3.

Other demographic characteristics analyzed include number of children in household, age of the children, metropolitan status of the household, number of household members, worker class. The results for these variables can be found in the Supporting information.

To summarize, while clusters are to some degree demographically distinct, there is still significant variability within each cluster. While more advanced statistical analysis would help link demographics and clusters, our impression is that there would still be still be significant variability not explained by demographics. This suggests that data on end-use consumption per device using smart home systems show promise to identify heterogeneity in the energy using behaviors.

3.5. Multi-year results

Since ATUS data is available for the years 2003–2013 we analyzed heterogeneity in time-use pattern for all the 11 years. Both time-use trends and socio economic-characteristics have remained consistent for the past 11 year. Multi-year results are available in the Supporting information.

3.6. Caveats and uncertainty

One key caveat is that the television time-use per respondent reported in ATUS may be underreported. ATUS does not report on secondary activities. In other words, respondents could be doing two activities at the same time (e.g., cooking and watching television, taking care of children and watching television) and the respondent could consider television activity as secondary activity. Additionally, television "On Time" when respondent is away from the television is also not recorded in ATUS.

This model does not represent the television energy use of the entire household, only that of the device watched by the survey respondent. This is because the ATUS only covers the behavior of the respondent, not the entire household and does not include television-watching time of household members less than 15 years old.

The analysis does not account for differences in the televisions ownership of the clusters. We assume all televisions are typical. Accounting for differences in televisions owned would increase heterogeneity, but the variability between clusters would only increase if there were differences in the types of televisions owned in different clusters. Such differences could be significant, since clusters 1 and 2 have higher median income, they might own larger televisions. On the other hand, since cluster 3 watches more television, member may devote a larger share of their income to purchasing newer and larger models. Limited survey data does not allow us to pursue this question of differences in television models.

It is also important to note that time-use based approaches work best when the "On time" of the device correlates with the amount of time of a reported activity. Energy use of white goods such as refrigerators and washing machines dryers, for example, does not map well to time use. For these devices, data from other survey instruments such as RECS are more appropriate.

4. Conclusions and policy implications

Our results indicate that accounting for customer heterogeneity could significantly improve the benefit-cost ratio of utility programs to incentivize energy efficiency. Every adoption by a customer in Cluster 3 saves approximately triple the total energy compared to an average customer. Utilities are also often motivated to reduce peak energy usage and there are dramatic differences in peak profiles between clusters. It is thus in the interest of utilities to identify and target those customers whose adoption will benefit them most.

Bearing in mind that benefits of preferential adoption of televisions by Cluster 3 will vary by utility, we illustrate via an estimate of potential monetary savings for Pacific Gas and Electric (PG&E) in California. The monetary savings is calculated as the difference in electricity wholesale purchases for distributing 644,000 energy efficient televisions (14% of PG&E residential accounts) uniformly among the population vs targeted adoption by Cluster 3. While the number of televisions in each household is reported as 2.6 (Urban et al., 2014), we assume a conservative case where only the primary television is replaced. The television watching patterns of residents for the uniform distribution follows

the average pattern shown in Fig. 4. Assuming energy efficient televisions draw 52 W less power (EPA, 2015), preferential adoption by Cluster 3 reduces power consumption in the PG&E area depending on time of day, up to a maximum of 20 MW, at 3 PM. Using daily profiles of wholesale electricity prices, this reduction in load saves PG&E $2–3 million annually. Given that consumers tend to own televisions for 7 years, this cost savings translates into utilities being willing to pay up to $21–33 per customer for preferential adoption by Cluster 3.

How can utilities identify and target sub-populations for energy efficiency programs? To first discuss identifying sub-populations, there are tradeoffs between the accuracy of identification and costs. We propose three approaches, in increasing order of cost to the utility and quality of data.

The least expensive method to identify sub-populations is to use ATUS and other public data to associate Cluster 3 consumers with demographic characteristics of their customers. While the data is free, as seen in Section 3.4, Cluster 3 does not align perfectly with demographic characteristics. For example, elderly customers are far more likely to be in Cluster 3, but many are not. While ATUS data does not inform use of most appliances, a similar analysis as done here but for the Residential Consumption Energy Survey (RECS) would inform customer heterogeneity in thermostat settings, lighting, and use of washers and dryers.

A second approach is that utilities could conduct their own surveys of appliance use. This would allow utilities to map energy relevant behavior to individual customers instead of demographic groups, but incur the cost to administer the survey. Also, there is a question of the accuracy of self-reported information.

Thirdly, smart sub-metering combined with surveys would increase the accuracy of data and enable better verification of the benefits of targeting programs. Starting from least to most expensive, three metering solutions are temporary smart meter, permanent smart meter, and smart meter with plug-load sub meters. The temporary smart meter approach is being tested in the U.K. by the University of Cambridge's Environmental Change Institute (ECI). The program involves combining a 3-day loan of a smart meter with a time-use survey (Environmental Change Institute, 2016). While there are hopes that Non-Intrusive Appliance Load Monitoring methods (NLIM) can leverage smart meters to inform appliance level load information, the methods still have problems with accuracy (Carrie Armel et al., 2013). Separate plug load meters could remove the need for surveying customers, but involve additional hardware investment.

The above methods enable a utility to identify a subset of customers to target for an efficiency program. Strategies are needed to increase the adoption of the technology in the targeted population. Variable rebates and tiered communication are two possible strategies. With *variable rebates,* utilities would offer higher rebates to high-use customers for whom efficiency would deliver larger benefits to the energy system. There is a long history of utilities tailoring incentives by location to address specific infrastructure constraints, e.g. RG&E Control Your Savings program (RGE, 2015). In the demographic space, enhanced incentives for lower income and elderly populations are reasonably common. Tailoring an incentive to the benefits an individual household would deliver to a utility would be new, but the prior two examples show precedent for the principle.

Utilities can also use *tiered communication* to target distinguished segments of customers. Tiered communication means the degree and type of information varies according to customer type. In order of increasing expense, utility's means of customer communication are the following: website, email, modified utility bill, flyer mailed with utility bill, separate mailing, phone, and in person. A tiered communication strategy would allocate resources so as to encourage participation in those groups whose adoption most benefit the

utility. For example, for televisions, every consumer might receive brief information on the utility bill about the rebate, but cluster 3 customers might receive a phone call. In order to establish a customer dependent degree of savings, the application for rebate should ask simple questions to establish usage patterns.

We thus suggest that utilities engage in benefit-cost analysis of variable rebates and tiered communication strategies for energy efficiency programs. Currently, in the U.S., 26 programs provide rebates for televisions while around 200 and 500 programs are available for refrigerators and lighting respectively (EPA, n.d.). Re-evaluation of the programs would presumably affect the number and design of programs for each end-use technology. We do not demonstrate such an analysis here; this would require detailed and utility dependent data, not publicly available. We have, however, demonstrated the potential benefits of such an approach for televisions. Analysis of heterogeneity in energy use for other devices and appliances, e.g. heating and cooling systems, would presumably also reveal benefits of a more personalized approach to consumers.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2016.02.035.

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