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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.

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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

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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

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